Universities and the Rise of Services*

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Abstract: Structural transformation from manufacturing to services varies substantially across regions. Using U.S. regional data, we document that commuting zones with universities (i) experience faster growth in service employment, particularly in high-skill services, (ii) exhibit higher college wage premia, and (iii) account for a disproportionate share of newly emerging tasks. We develop a task-based theory of local structural transformation to examine two roles of universities: the supply of high-skilled labor and the creation of new tasks that generate skill-biased labor demand. Our theory and quantitative analysis suggest that the innovation channel plays a central role in jointly accounting for the rise of services and the higher skill premium in regions with universities. Overall, our framework provides microfoundations for skill-biased structural change and highlights the importance of higher education in shaping regional economic dynamics.

Key words: structural transformation, skill premium, new task, economic geography
JEL classification: R11, O11, I25

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1 Introduction

Structural transformation of the macroeconomy from manufacturing to services has been extensively studied, yet much less is known about how this transformation unfolds unevenly across regions within a country. Consider Detroit and Pittsburgh: both cities were historically reliant on manufacturing, yet they have experienced different economic trajectories in recent decades. Detroit, once the heart of the American automotive industry, has struggled to adapt to the service-oriented economy, resulting in economic decline and population loss. In contrast, Pittsburgh, once dependent on steel manufacturing, successfully transformed itself into a center for education, healthcare, and technology. These divergent outcomes raise a fundamental question: what drives the geographic variation in structural transformation?

A key distinction between the two cities lies in the presence of higher education institutions. Pittsburgh is home to leading research universities such as Carnegie Mellon University and the University of Pittsburgh, while Detroit lacks comparable institutions. As documented by Van Agtmael and Bakker (2016), Pittsburgh's transformation from a Rust Belt city into a "brain belt" hub illustrates how vibrant research universities can serve as engines of innovation, fostering new industries and expanding employment opportunities in high-value service sectors.[1]

In this paper, we ask whether and how universities in the local economy contribute to the structural transformation from the traditional manufacturing to the modern service economy. We present evidence that universities have a positive impact on the growth of the service sector, especially high-skill services, by studying the variation in the rise of services across US regions. In particular, regions with top universities are associated with stronger growth in employment share of high-skill services, higher skill premia, and disproportionate share of newly emerging tasks. We then develop a simple theory of local structural transformation and show that universities' contribution to the innovation of new tasks is crucial to understanding their role in the growth of the service sector and the higher skill premium. This process expands the variety of services and drives demand for high-skilled workers who specialize in tasks intensively used in high-skill services.

We begin by documenting a substantial variation in structural transformation trends across US commuting zones (CZs). While the majority of CZs experienced positive growth in the rise of services over the past four decades, we observe substantial geographic variation. Areas in the Northeast such as Boston and New York, the West such as the Silicon Valley, and the South such

[1] In Van Agtmael and Bakker (2016) [p. 27], "Each brain belt is a tightly woven collaborative ecosystem of contributors, typically composed of research universities, community colleges, local government authorities, established companies with a thriving research function, and start-ups, usually supported by a variety of supporters and suppliers, including venture capitalists, lawyers, design firms, and others. These different types of entities establish their own unique identity as they share knowledge, interact, form a community, grow, and improve."

as Austin show some of the most significant increases in service sector employment. In contrast, parts of the Midwest and interior regions lagged behind, experiencing more modest gains or even declines. Importantly, this variation cannot be attributed solely to differences between large and small cities or between urban and rural areas. Instead, these patterns are strongly correlated with the spatial distribution of colleges using data from the Integrated Postsecondary Education Data System (IPEDS). Motivated by this observation, we present several novel empirical findings linking local structural transformation to the presence of universities.

First, regions with four-year colleges have seen faster growth in the share of service sector employment. Between 1977 and 2016, CZs with a college saw a 6.5 percentage point higher increase in service employment share compared to those without one, primarily driven by the high-skill services. Conditional on the initial size of employment and sectoral employment composition as well as population density, CZs with higher-ranked top universities had the most substantial growth in the high-skill service sector. In particular, CZs with a top 100 university experienced an average of 5 percentage points higher increase in high-skill service employment share between 1977 and 2016, relative to those with universities ranked outside the top 440.

To address the endogeneity of university locations, we exploit the natural experiment of college site selections back in the 1800s following Andrews (2023) and Russell, Yu, and Andrews (2024) and identify the impact of universities. Comparing the winning and the runner-up counties in the same college-site selection experiment, we find that whereas the two groups had similar sectoral composition in the 1970s, the former have shown a larger increase in service employment over the recent four decades. This suggests that the presence of universities itself has likely shaped the geographically differential rise of services rather than economic size, initial economic structure or local amenities, which are simply correlated with university presence.

Next, we analyze the relationship between universities and local labor market dynamics, focusing on the evolution of skill premium and the emergence of new tasks, using data from the American Community Survey (ACS). Our findings are twofold. First, we find that the college/skill premium increased more in regions with a university than in those without. Since 1990, CZs with universities, especially those with good ones, have consistently exhibited higher skill premiums, suggesting that these areas have been the key drivers of the national rise in the return to skill. This result adds to the literature on the dynamics of the skill premium in the US (e.g., Katz and Murphy, 1992; Goldin and Katz, 2007; Acemoglu, 2003) and on urban-rural disparities in skill premium (e.g., Glaeser and Maré, 2001; Gould, 2007; Baum-Snow and Pavan, 2012) by highlighting the role of universities in shaping the regional variation of skill premium independent of existing explanations.

Second, we show that the emergence of new tasks in response to technological innovation, as documented by Autor et al. (2024), is disproportionately concentrated in regions with uni-

versities. For instance, for occupations such as "computer systems analysts and scientists" and "computer software developers" that saw a surge in new job titles in the 1990s, reflecting the broader expansion of the IT sector, their employment shares are significantly higher in CZs with a top university. More generally, by constructing a "New Task Index" which approximates the share of employment in new titles for each CZ, we find that new tasks are concentrated in CZs where a (good) university exists. This observation suggests that universities not only supply skilled labor but also play a central role in the creation and diffusion of new tasks in the local labor market.

We formalize these mechanisms through a simple theoretical framework and and evaluate their significance via a quantitative spatial model. The simple theory links differential skills, tasks, and sectors and shows how universities shape the difference in local structural transformation via the two new channels discussed above. Workers with different skills perform different tasks according to their comparative advantages: low-skilled workers perform low-ranked tasks, such as cleaning and machine assembly, while high-skilled ones perform high-ranked ones, such as management and R&D. As a result, the marginal cost of each task depends on the task assignment between the two types of workers. The manufacturing and high-skill services sectors use tasks as inputs with different input shares. In the high-skill service sector, firms adopt high-ranked tasks (e.g., management) as well as other lower-ranked tasks (e.g., maintenance, cleaning) to produce a differentiated service, which defines the endogenous task intensities within services. The equilibrium in this economy is characterized by the assignment rule of tasks to workers and the wage ratio between high and low-skilled workers, given their relative sizes and the set of tasks.

Our theory predicts that regions transform from manufacturing to services at different rates when they have different patterns in (i) supplying high-skilled workers, and (ii) creating new tasks. This implication illustrates the role of universities in explaining the local structural transformation as suppliers of high-skilled workers *and* hubs for innovating new tasks. For example, top US universities in Silicon Valley and the Research Triangle have pumped high-skilled engineering and computer science graduates into the local economy and also created new tasks and industries, such as researchers in AI and social network services. Together, these two roles have driven the local structural transformation from the traditional manufacturing sector to the high-skilled task-intensive sector, including services, without drastically changing low-skilled worker tasks.

Importantly, these mechanisms have distinct implications for the local labor market's skill premium, echoing the race between education and technology described in Goldin and Katz (2007). An increased supply of high-skilled workers shifts tasks from low-skilled to high-skilled workers but lowers the skill premium. In contrast, by generating new tasks, regions with uni-

versities stimulate higher demand for high-skilled workers, thereby increasing the equilibrium skill premium. The observation that regions with universities predominantly drive the rising skill premium suggests that the innovation effect may outweigh the talent supply effect.

To quantify the mechanisms through which universities shape the local rise of services and local labor market dynamics, we extend the stylized theory to a heterogeneous-regions spatial economy that accounts for labor mobility and the local housing market. Different from the simple theory, mobility of high-skilled workers across regions generates a positive feedback loop, leading to further growth of the service sector: An expansion of tasks is associated with more differentiated services, which lowers the total price index. Moreover, the creation of new tasks raises the equilibrium relative wage of high-skilled workers, therefore raising their real income. As a result, regions with universities attract more high-skilled workers from other regions and increases their supply, accelerating the shift of the economy from manufacturing to services. Lastly, we quantify this model to assess the impact of higher education on the rise of services in the US economy over the past decades.

This paper contributes to the literature on structural transformation by documenting new facts about its geographic variation within a country. The shift from agriculture to manufacturing and then to services has been extensively studied in the macroeconomic literature (e.g., Fisher (1939); Kuznets (1966); Barro and Sala-i Martin (2004); Buera and Kaboski (2012); Herrendorf, Rogerson, and Valentinyi (2014)), and various mechanisms explain structural transformation in the aggregate economy, including exogenous productivity growth (e.g., Baumol 1967; Matsuyama 1992; Laitner 2000; Ngai and Pissarides 2007; Huneeus and Rogerson 2024) and non-homothetic demand across sectors (e.g., Kongsamut, Rebelo, and Xie 2001; Matsuyama 2009; Comin, Lashkari, and Mestieri 2021). At the sub-national level, Caselli and Coleman II (2001) studies aggregate structural transformation and regional convergence together; Desmet and Rossi-Hansberg (2009, 2014) develop a model of technology diffusion to investigate the spatial pattern of structural transformation; Eckert and Peters (2022) studies the interaction of exogenous comparative advantages across locations and the aggregate productivity growth in the agricultural sector; Takeda (2023) provides the quantifiable model on the structural transformation across geography, which is used to evaluate the impact on workers' mobility. In this paper, we focus on the role of universities and provide new empirical and theoretical insights into the endogenous mechanism of the different rates of structural transformation from manufacturing to services across geography.

Our theory of labor skill and task assignment is closely related to Ricardian trade model, which is applied to labor research, such as Acemoglu and Autor (2011), to study how different skill groups perform imperfectly substitutable occupations.[2] We view the expansion of tasks in

[2]The task-based approach in the labor market is defined by Autor, Levy, and Murnane (2003) and it is related to job polarization with a reduction of routine jobs (Goos and Manning 2007). In recent, Acemoglu and Restrepo (2019)

our theory as similar to the idea of product diversity along with structural transformation (Romer 1987; Ciccone and Matsuyama 1996; Fafchamps and Helms 1996). In addition, the approach has been supported by evidence that points to an increasing number of workers in new work in locations initially dense with college graduates (Lin 2011) and the positive association between new job titles and employment growth in US (Autor et al. 2024). We develop the parsimonious model of the task-skill assignment to show how new tasks promote structural transformation and how the geographic variation of universities and the mobility of workers account for the growth of services. Among others, our theory is reminiscent of Acemoglu and Restrepo (2018) and Acemoglu and Restrepo (2022), which present task-based models to understand the effects of automation and new tasks. Yet, our model focuses on the effect of introducing new tasks and the spatial variation of its impact on structural transformation.[3]

Lastly, this paper contributes to the literature examining the role of universities in regional economic growth, (see for example, Valero and Van Reenen 2019; Nimier-David 2022; Hausman 2022; Alon, Capelle, and Matsuda 2022; Babina et al. 2023; Andrews 2023; Howard, Weinstein, and Yang 2024), the impact of college expansion on the local labor market (e.g., Carneiro, Liu, and Salvanes 2023), the relationship between human capital and regional development (see for example, Acemoglu and Dell 2010; Gennaioli et al. 2013), and the interaction of education and innovation in driving aggregate productivity (Akcigit, Pearce, and Prato 2025). Our paper presents (i) new empirical evidence on the impact of universities on the structural transformation in the local economy from manufacturing to services and (ii) a simple theory and quantifiable model for connecting the location of universities and the geographic variation in structural transformation and college wage premiums.

The rest of this paper proceeds as follows. Section 2 details the data used in our empirical analysis. In Section 3, we present new facts relating universities to the regional growth of service employment and skill premium. In addition, we decompose the structural transformation to understand the sources of its geographical variation. Section 4 develops a new theoretical framework of the assignment model of skills, tasks, and sectors and discusses universities' role in local structural transformation. The theory is extended to a multi-region economy in Section 5, calibrated using US data in Section 6. In Section 7, we calibrate the model to quantify the mechanisms underlying local structural changes. Finally, Section 8 concludes.

point out that automation can increase total labor demand if it creates new tasks for workers.

[3]In this respect, our theoretical framework offers a micro foundation for the "skill-biased structural change," which is often exogenously assumed in existing models (Buera et al. 2022).

2 Data

In this section, we describe the datasets used in our empirical analysis and provide descriptive statistics of the overall and regional structural transformation in the US, together with the spatial distribution of universities.

2.1 Data Description

Local Labor Market We construct the dataset for the US local labor markets from two sources: County Business Patterns (CBP) and the American Community Survey (ACS). CBP data for the period 1986–2016 were obtained from the U.S. Census Bureau, while data for 1977–1985 were sourced from the ICPSR.[4] Following the imputation method in Acemoglu et al. (2016), we construct a dataset of annual county and CZ-level employment and establishment counts at the 4-digit 1987 SIC industry level. Although the CBP data provide broad coverage of firms across local labor markets and industries, they do not include detailed micro-level information on wages or the occupational and skill composition of the workforce—factors essential for analyzing local economic conditions beyond aggregate measures. To address this limitation, we supplement the CBP data with aggregated individual-level information from the ACS. Using the survey-provided individual weights, we compute average annual wages and total employment by geographic location, industry, occupation, and educational attainment.[5] Appendix Table D.1 demonstrates that employment measures from the ACS are broadly comparable to those from the CBP, despite the former being based on individual-level survey responses. Figure D.1 further illustrates the close alignment between the two sources in capturing broad trends in structural transformation. This consistency allows us to leverage the richer occupational and skill-level detail available in the ACS to conduct a more granular analysis of changes in structural transformation.

Sectors We primarily focus on three sectors throughout this paper: manufacturing (SIC 2000–3999), high-skill services, and low-skill services. Our definition for high vs low-skill service sectors broadly follows the literature (for example, Buera et al., 2022), with the former including "Finance, Insurance and Real Estate (FIRE)," "Business Services," "Health Services," "Legal Services," "Educational Services," "Engineering, Accounting, Research, Management, and Related Services," and the latter including the remaining service sectors such as "Retail Trade" and "Personal Services." Where necessary, we also examine the service sector, which combines both high-skilled and low-skill services, and the construction sector, defined by SIC codes 1500–1799.

[4]Links to CBP datasets: https://www.census.gov/programs-surveys/cbp/data/datasets.html for Census and https://www.icpsr.umich.edu/web/ICPSR/series/00022 for ICPSR.

[5]Our analysis is restricted to individuals who were actively employed and worked between 50 and 52 weeks in the prior year.

Occupations and Skills We obtain data on local and industry-level occupations and skills from from ACS for the years 1950, 1970, 1980, 1990, 2000, and annually from 2005 to 2016, which are available in IPUMS. These individual-level survey data provide detailed information on educational attainment, employment status, occupation, industry, and wage income. To classify occupations, we adopt two complementary approaches. First, following Autor and Dorn (2013), we categorize occupations into "abstract," "routine," and "manual" based on their task intensity. Second, we employ the Nam-Powers-Boyd scores,[6] which quantify occupational skill intensity. In our context, "skill" is proxied by educational attainment at the individual level; for example, a college graduate is assumed to possess higher human capital than a high school graduate. To assess the role of universities, we construct a binary skill indicator equal to one for individuals who have completed a four-year college degree or higher, and zero otherwise. We then aggregate the individual-level data by county or commuting zone (CZ) within each occupation and skill category to generate measures of total local employment and average local wages by occupation-skill cell.

Universities Data on US universities are drawn from the Integrated Postsecondary Education Data System (IPEDS), which covers the universe of accredited higher education institutions from 1980 to 2022, excluding the years 1981 to 1983. We construct a panel dataset by merging annual files using each institution's unique identifier. The resulting dataset includes rich institutional-level information on location, type, enrollment, graduation rates, and financial metrics such as grant disbursements and expenditures. Given our focus on the role of universities in generating high-skilled labor and facilitating task creation, we broadly classify institutions into four-year colleges and all others. To proxy for institutional quality, we categorize universities based on their rankings in the 2016 U.S. News & World Report Best National Universities list.[7] While historical rankings are not consistently available, we use the 2016 rankings as a proxy for institutional quality over time, given the relative stability of rank groupings despite annual fluctuations in individual positions. The ranking includes approximately 440 institutions, which we group into five categories: "Rank 1" (ranks 1–100), "Rank 2" (101–200), "Rank 3" (201–300), "Rank 4" (301–443), and "Others."

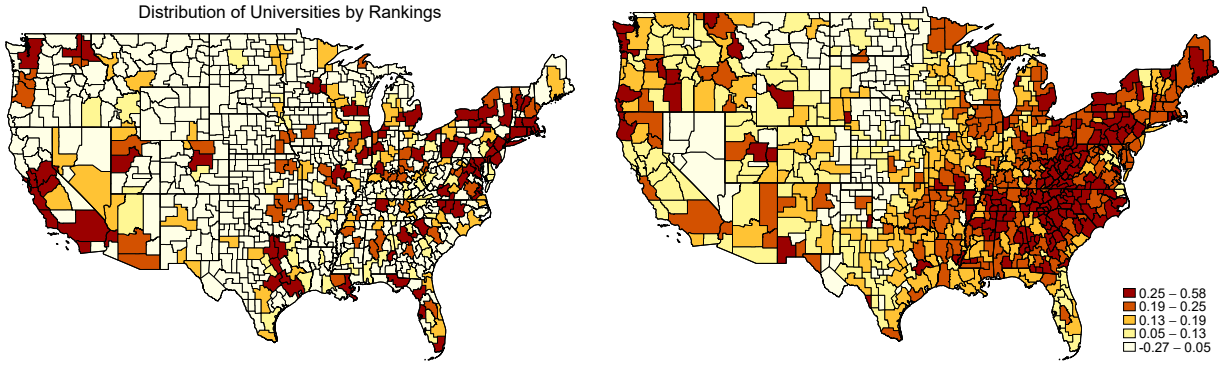
Merged Dataset To build a consistent regional dataset that can be compared across time and regions, we harmonize the raw data using standardized classification systems for geographic location, industry, and occupation, following the crosswalks developed in Autor and Dorn (2013) and Autor, Dorn, and Hanson (2019).[8] For geographic harmonization, we map Census State Economic Areas, Census County Groups, and ACS Public Use Micro Areas to 1990 CZs, which forms

[6] Available at http://www.npb-ses.info/.

[7] Available at https://www.usnews.com/best-colleges/rankings/national-universities.

[8] These crosswalks are available on David Dorn's website https://www.ddorn.net/data.htm.

Figure 1: Geography of US Colleges and Change in the Service Employment Share



(a) US Colleges by Rankings **(b)** Change in Employment Share of Services

Notes: Panel (a) plots the distribution of colleges by their 2016 US News rankings. CZs in the US are divided into five groups: from dark to light, rank=1; rank=2; rank=3; rank=4; and others. Panel (b) illustrates the change in the service sector employment share between 1977 and 2016 across US CZs, grouped into five quintiles based on the magnitude of the change. Data source: US News Best National Universities Ranking and CBP.

our baseline geographic regions.[9] Industries are converted into a unified 1987 Standard Industrial Classification (SIC) 4-digit code system using a weighted crosswalk procedure. Occupational codes from the Census (*occ*) are mapped to the *occ1990dd* classification as in Autor and Dorn (2013). The resulting regional panel dataset contains, for each CZ, information on industry, occupation, skill (education), employment, wages, and the number of establishments. In addition, we include a binary indicator for the presence of a four-year college ("college" dummy), and a categorical variable capturing the rank group of the highest-ranked university within the region.

2.2 Descriptive statistics

These data offer valuable insights into local economic dynamics over the past decades. To begin, we present descriptive facts on national and local sectoral employment shares derived from both CBP and ACS data, along with the spatial distribution of colleges categorized by ranking group.

First, consistent with a large body of literature, our regional data reveal clear patterns of aggregate structural transformation from manufacturing to services. Employment in the manufacturing sector declined markedly between 1980 and 2016, with average employment shares falling from approximately 0.29 to 0.10 across both the CBP and ACS data. CZs lacking a four-year college consistently exhibit higher manufacturing employment shares than those with one, suggesting a potential role of higher education in shaping local labor market compositions. Conversely, the service sector experienced a substantial expansion over the same period, with average employment shares rising from approximately 0.59–0.64 to 0.74–0.83. CZs with a college generally display higher service employment shares than those without. These trends not only

[9] In exercises that require the use of county-level data, such as in Sec 3, we rely directly on raw CBP data.

reaffirm the nationwide shift from manufacturing to services, as widely documented in the literature, but also emphasize the role of higher education in contributing to the spatial heterogeneity of structural transformation—an issue central to our analysis.

Second, the geographic distribution of universities exhibits substantial heterogeneity across regions. Panel (a) of Figure 1 illustrates the spatial allocation of U.S. colleges by rank across CZs in 2016, based on data from the U.S. News Best National Universities Ranking. The map employs a gradient shading scheme, where darker tones denote CZs hosting higher-ranked institutions (Rank 1), and lighter tones indicate zones with lower-ranked universities or none (Rank 5). This spatial visualization highlights pronounced regional disparities in the quality of higher education institutions. Higher-ranked universities are disproportionately concentrated in the Northeastern and Western regions, although several top-ranked institutions are also present in parts of the Midwest and the South.

Third, we observe substantial regional variation in the rise of the service sector. Panel (b) of Figure 1 depicts changes in the service sector employment share across CZs from 1977 to 2016. The figure reveals considerable heterogeneity in the magnitude of structural transformation. The Northeast and Mid-Atlantic regions—including metropolitan areas such as New York City, Philadelphia, and Boston—experienced pronounced increases in service employment, with gains exceeding 25 percentage points in some CZs. In contrast, regions in the South, Mountain West, and Great Plains generally saw more modest increases, and in some cases, declines. We hypothesize that the presence of colleges is a key factor driving this regional heterogeneity in structural transformation, a proposition we examine in greater detail in the following section.

3 Motivating Evidence

In this section, we begin by presenting four novel empirical patterns related to local structural transformation and labor markets, which point to a potential role for universities in shaping local economic dynamics. We then leverage historical college site selection experiments conducted between 1839 and 1954 to identify the causal impact of universities on the growth of the service sector. Finally, we decompose the observed changes in service employment shares to isolate the key components driving local structural transformation.

Fact #1: Service employment growth is more pronounced in CZs with colleges, especially those with a top-ranked one.

We present descriptive evidence on the heterogeneity of structural transformation across CZs. We begin by comparing CZs based on the presence or absence of a four-year college or university. Panel (a) of Figure 2 displays the average change in sectoral employment shares between

1977 and 2016 for these two groups. Over this period, the average increase in the service sector employment share was 17.8 percentage points in CZs with a university, compared to 11.3 percentage points in those without. This cross-regional disparity is evident in both high-skilled and low-skill service sectors; however, the growth is concentrated in high-skill services, while employment shares in low-skill services remained largely unchanged, particularly in regions lacking a university. In contrast, manufacturing sectors, especially the low-skill one, experienced a substantial decline in its employment share, with the decline being more pronounced in CZs that host a university.

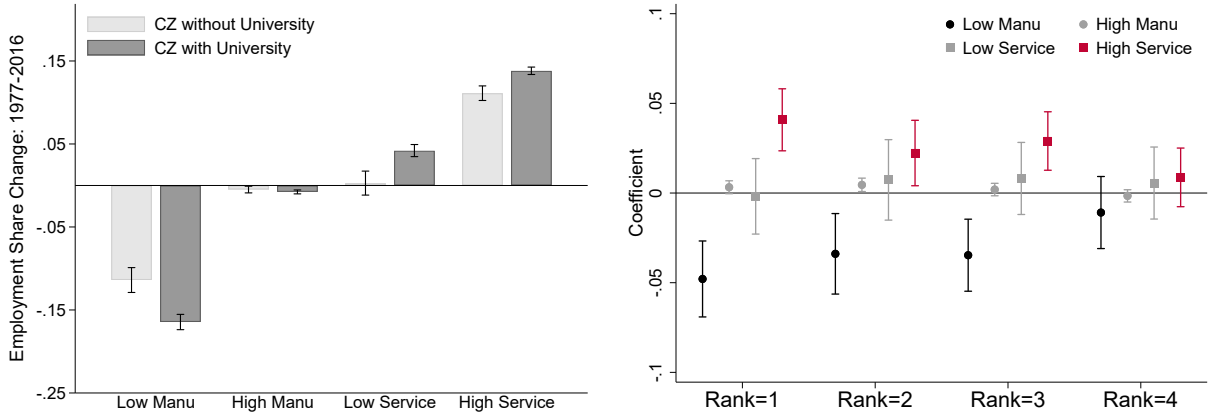
Not all universities are alike. We next examine the role of university quality. It's also worth noting that structural transformation may be shaped by other regional characteristics such as the size of the economy and population density. In addition, regional differences in initial industrial composition may interact with sectoral shocks, such as increased import competition, in shaping sectoral employment dynamics. To account for these factors, we estimate regressions of changes in employment shares in the manufacturing and service sectors on indicators for the rank of the highest-ranked university in each CZ, controlling for total employment and sectoral employment shares in the base year of 1977, as well as CZ-level population density.

Panel (b) of Figure 2 plots the estimated coefficients on university rank groups, interpreted relative to the omitted category of "Others" (i.e., CZs with the lowest or no ranked university). The results indicate that CZs with higher-ranked universities—particularly those ranked in the Top 300—exhibit statistically significant differences in structural transformation, with larger declines in low-skill manufacturing and greater expansions in high-skill service. In contrast, growth differences in low-skill service and high-skill manufacturing sectors across regions with different rank groups are minimal. These findings suggest that the presence of a higher-ranked university is associated with a more pronounced shift from manufacturing to high-skill services, even after accounting for initial employment levels and industrial composition. Our results also highlight that the differential expansion of the service sector across CZs with varying university ranks is primarily attributable to growth in high-skill service employment. This empirical pattern motivates a differential treatment of high- and low-skill services in the modeling framework developed in the subsequent analysis.[10]

Identification A potential concern is the endogeneity of university location. Consequently, the observed differences in structural transformation may be driven by confounding factors unrelated to the causal impact of universities, such as initial economic size, pre-existing industrial structure, or other locational characteristics that are correlated with both the presence of a university

[10]College-linked employment may take an exceptional weight in the (high-skill) service sector in smaller regions, such as small college towns. In Appendix E.2, we show that the result in Figure 2 holds when the education service sector is removed from the sample.

Figure 2: Universities and Local Structural Transformation



(a) Average change in sectoral employment share in CZs with and without universities

(b) Change in sectoral employment share in CZs by university rankings

Notes: These figures show the average changes in sectoral employment share between 1977 and 2016 across CZ groups. In Panel (a), CZs are grouped by the existence of a four-year university. Bars represent the average change of sectoral employment share in each CZ group, and the vertical lines represent their 95 percent confidence intervals. In Panel (b), we group CZs by the existence of a university that falls into each ranking group: "1-100 (rank=1)," "101-200 (rank=2)," "201-300 (rank=3)," "301-440 (rank=4)," and "Others." We regress changes of employment share in the manufacturing and service sectors between 1977 and 2016 on a set of indicators on the rank group of the top university in each CZ, the logarithm of total CZ employment in 1977, the sectoral employment share in 1977, and CZ-level population density (log population per mi^2). This figure plots the coefficients on these ranking indicators by sector, together with their 95 percent confidence intervals. Data sources: CBP, IPEDS, US Gazetteer Files, and US News Best National Universities ranking.

and subsequent economic outcomes. To identify the causal impact of hosting a university on local structural transformation, we adopt the empirical strategy proposed by Andrews (2023) and Russell, Yu, and Andrews (2024), which compares counties that were selected to host a university with those that were runners-up in the same site-selection process. These college siting experiments, conducted between 1839 and 1954, provide plausibly exogenous variation in university placement.[11]

In particular, we estimate the following equation:

$$\Delta \ell_c^j = \beta^j \text{Treatment}_c + \gamma_1^j \ell_{c,1977}^j + \gamma_2^j \log L_{c,1977} + \gamma_e^j + \epsilon_c^j, \tag{1}$$

where j represents the sectors (manufacturing or services). The dependent variable $\Delta \ell_c^j$ is the change in employment share for sector j in county c from 1977 to 2016: $\Delta \ell_c^j = \ell_{c,2016}^j - \ell_{c,1977}^j$. Since there is no relocation of colleges in the period, Treatment_c is time-invariant for a specific county, taking a value of 1 if county c was the winner of a college site selection and 0 if it was a runner-up in the same site selection experiment. The initial sectoral employment share $\ell_{c,1977}^j$

[11] In our benchmark analysis, we exclude colleges that subsequently relocated after the initial site-selection decision. A robustness check including these institutions, using their new location as the treated county, yields similar results. Details on the data can be found in Appendix E.5.

Table 1: Sectoral Employment Shares Changes: Winner versus Runner-Up Counties

	Manufacturing	Service
Winning Site	-0.009**	0.012**
	(0.005)	(0.005)
Sectoral Employment Share in 1977	-0.618***	-0.629***
	(0.036)	(0.038)
Log Total Employment in 1977	-0.013***	0.018***
	(0.002)	(0.002)
Observations	930	932

Notes: This table reports the coefficient estimates of equation (1). Robust standard errors clustered by county are shown in parentheses. ***, ** and * indicate significance at the 1, 5 and 10 percent levels, respectively.

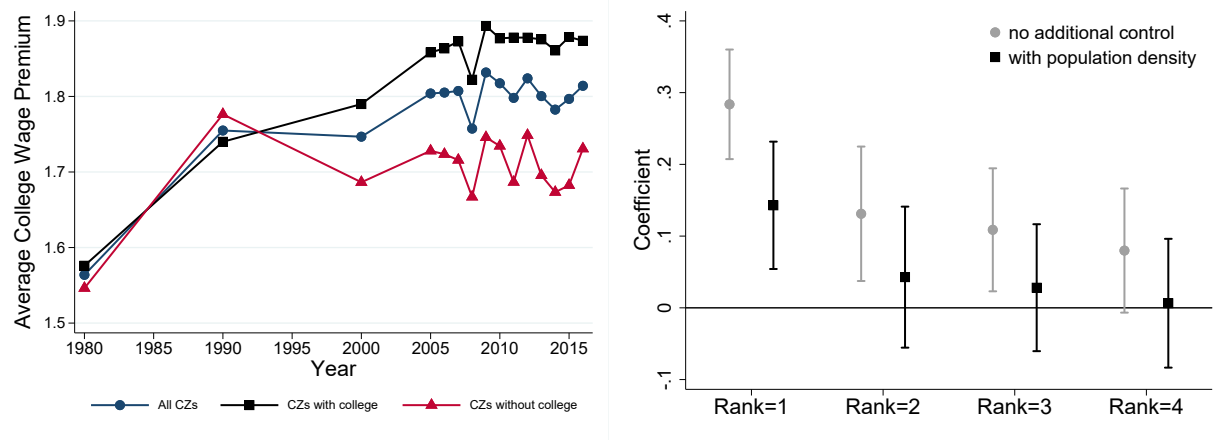
and the initial log total employment $\log L_{c,1977}$ control for sectoral composition and economic size at the start of our analysis period, considering the potential differential growth trajectories between winning and runner-up counties over the decades. They help ensure that the estimated long-run effect of winning a college site on employment share changes is not biased by pre-existing differences. γ_e^j stands for the experiment fixed effects so that comparisons are between winning and runner-up counties for the same college. This setup allows for a handful of cases where a county that had been rejected by one college later on was chosen for another university. For example, Maricopa County won the selection for Arizona State University but lost to the University of Arizona.

The identification assumption of our empirical analysis is that the winning and runner-up counties are similar along observed and unobserved dimensions. As documented in Andrews (2023) and Russell, Yu, and Andrews (2024), this assumption is likely to hold; in fact, some of these selection experiments were even randomly assigned. Table 1 presents the coefficient estimates together with the standard errors clustered by CZ, considering the potential correlation of economic activities within a region. Our main parameters of interest, β^j, are precisely estimated to be negative for the manufacturing sector and positive for the service sector. This result is consistent with our descriptive evidence: relative to runner-up counties, counties selected to host a university experienced a greater decline in the manufacturing employment share and a larger increase in the service employment share. Moreover, we find that initial economic conditions play a meaningful role in shaping the heterogeneity of structural transformation across counties.

Fact #2: On average, the skill premium increased in CZs with colleges relative to those without.

Panel (a) in Figure 3 shows the average skill premium, or college wage premium, across CZs with and without a four-year college, from 1980 to 2016. The line with squares, representing the

Figure 3: Skill Premium Changes by Location



(a) Skill Premium in CZs with and without University

(b) Relative Skill Premium across CZs

Notes: Panel (a) plots the skill premium (college wage premium), averaged across all CZs, CZs with college and without, between 1980 and 2016. Panel (b) plots the estimates of the coefficients and their 95 percent confidence intervals for the regression of CZ-level changes in skill premium between 1980 and 2016 on a set of indicators on the rank group of the top university in each CZ, with no additional control or with CZ-level population density (log population per mi^2). The coefficient on population density is significantly positive. Data source: ACS, US Gazetteer Files and US News Best National Universities ranking.

overall average across all CZs, indicates a general increase in the skill premium between 1980 and 2005, consistent with existing studies (e.g., Goldin and Katz, 2007). After a significant decline and reversal during the Great Recession, it remained relatively stable, with only minor fluctuations.

We extend this well-documented national trend in rising skill premiums by disaggregating CZs based on the presence of a four-year college. In CZs with a college, the skill premium exhibits a clear and persistent upward trajectory throughout the period. Between 1980 and the early 2000s, these regions experienced a steady and faster-than-average increase in the skill premium relative to national trends. Although the upward momentum plateaued following the Great Recession, the skill premium in these CZs remained well above the levels observed in the 1980s and 1990s, as well as above those in regions without a college presence. In contrast, CZs without a college followed a markedly different path. While the skill premium in these regions initially rose at a pace comparable to—or even exceeding—that of CZs with a college, it began to decline around 1990, with only sporadic periods of modest recovery. Since 2000, the skill premium in non-college CZs has consistently lagged behind that of college CZs. The growing divergence between these trajectories over time underscores a widening regional gap in the returns to skill. It also suggests that local labor markets with colleges may have primarily driven the widely documented upward trend in skill premiums.

Similar to the analysis above, we examine how changes in the skill premium vary across

regions with universities of differing ranks. Panel (b) shows that between 1980 and 2016, regions hosting universities ranked within the top 300 experienced significantly larger increases in the skill premium compared to those with lower-ranked or no ranked institutions. The most pronounced rise is observed in CZs with top 100 universities. This pattern closely parallels the results on local structural transformation, reinforcing the notion that the quality of higher education institutions plays a critical role in shaping regional labor market dynamics.

Fact #3: New tasks emerge predominantly in regions with colleges.

Autor et al. (2024) document that new work emerges in response to technological innovation. We build on their analysis by examining the geographical distribution of new occupation titles. While their dataset provides information on the number of new titles by occupation and year, it does not include employment counts at the title level or the geographic location of these new titles. To address this limitation, we adopt an indirect approach. Specifically, we use Autor et al. (2024)'s data to compute a "new title share" for each occupation-year pair, capturing the relative intensity of new title creation within occupations over time. These shares offer insight into which occupations experienced the greatest influx of new job titles in a given year. We then ask: where are these high–new-title-intensity occupations geographically concentrated?

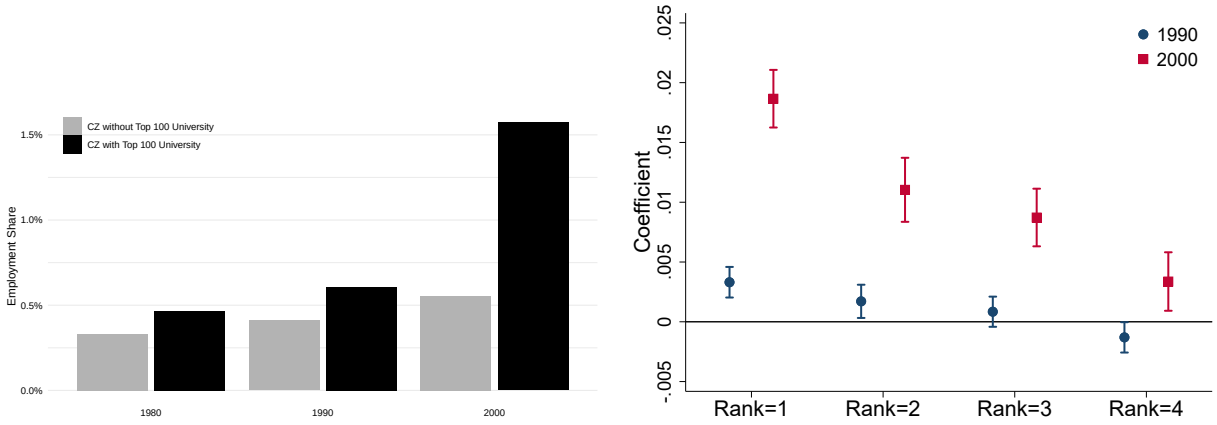
Using occupation-level employment data from the ACS, we may estimate the difference in employment shares by occupation and year between CZs with and without a university presence. Figure 4a presents the employment share in IT-related occupations, including "computer system analysts and computer scientists" and "computer software developers", in 1980, 1990, and 2000. Across these years, these occupations were among the top-ranked by the share of new titles within each occupation, likely due to the rapid growth of the IT sector during the 1980s and 1990s. More importantly, these occupations exhibit significantly higher employment shares in CZs with a top university, suggesting that occupations experiencing the most rapid expansion in new job titles tend to be disproportionately concentrated in regions hosting higher education institutions. This empirical pattern motivates our modeling assumption that universities function as hubs of innovation and play a central role in the creation of new tasks.

As an alternative piece of evidence, we propose a "New-Task Index":

$$\text{New Task}_{it} = \sum_{o} \frac{L_{iot}}{L_{it}} \frac{N_{ot}^{\text{New}}}{N_{ot}}, \tag{2}$$

where the first term, L_{iot}/L_{it}, represents the share of employment in occupation o at location i, computed using ACS data. The second term, $N_{ot}^{\text{New}}/N_{ot}$, captures the new titles share within each occupation o. This index is an approximate measure of the share of employment in these new titles by region and year. Conceptually, a location that has many occupations with both high

Figure 4: New Tasks by Location



(a) Employment Share in IT-Related Occupations

(b) New Task Index

Notes: Fig 4a plots the employment share in IT-related occupations in the years 1980, 1990, and 2000, including "computer system analysts and computer scientists" and "computer software developers." Data source: ACS. In Panel (b), we show the geographic variation in the "New-Task Index" (2) across CZ groups. We group CZs by the existence of a university that falls into each ranking group: "1-100 (rank=1)", "101-200 (rank=2)", "201-300 (rank=3)", "301-440 (rank=4)", and "Others." We regress this index for 1990 and 2000 on a set of indicators on the rank group of the top university in each CZ, controlling for CZ-level population density. Fig 4b plots the coefficients on these ranking indicators, together with their 95 percent confidence intervals. Data sources: Autor et al. (2024) and US News Best National Universities ranking.

employment share and high new titles share is where employment in new tasks is concentrated. Our goal is to show whether this index varies with the existence of a (top) university in that region. To do so, we run a regression similar to Panel (b) of Figure 2 and 3, and compare this index across each ranking group. Results for 1990 and 2000 are shown in Figure 4b. For both years, CZs with top universities are associated with significantly higher concentration of new tasks, which is consistent with the message conveyed in Figure 4a. And the difference across regions has dramatically increased between these two years.

4 A Task-Based Theory of Local Structural Transformation

We present a simple theoretical framework to provide new insights into (i) the relationship between skills, tasks, and sectors in the local economy, and (ii) how higher education and research can accelerate structural transformation through changes in task content by skill and sector. In Subsection 4.1 and 4.2, we lay out the model environment and define the competitive equilibrium. Subsection 4.3 provides comparative statics for the key variables in the model. Subsection 4.4 explains how this simple model provides new insights into structural transformation, which are connected to the empirical findings in Subsection 4.5. Subsection 4.6 discusses how the model

mechanism relates to and differs from existing ones in the literature. Further details of the model are presented in Appendix A.

4.1 Setup

We consider a single economy embedded in a large economy. There are two types of agents indexed by $i \in \{\ell, c\}$, where superscript ℓ refers to workers without a college degree (non-college graduates) and c stands for those who have received higher education, college graduates. The mass of each type in this economy is given by L_ℓ and L_c, respectively. All agents inelastically supply one unit of efficient labor. The labor market is competitive, and wages are given by w_ℓ and w_c for each type of worker. There are two types of products labeled as manufacturing goods and services.The manufacturing goods are homogeneous and freely tradable in a large economy, whereas services are non-tradable. We assume that workers of both types spend a share α of their income on services and $1-\alpha$ on manufacturing goods.

Tasks Performed by Individuals Tasks are horizontally differentiated, for example, car assembly, weaving textiles, constructing housing, and AI research. They are indexed by $j \in [0, J]$, where J denotes the upper bound of the set of existing tasks. This set of tasks expands as new tasks are introduced in the economy. Without loss of generality, we assume $J > 1$. Production of these tasks only requires efficient labor: one unit of efficient labor provided by type i labor produces $z_i(j)$ units of task j. College graduates can, in principle, perform any task, that is, $z_c(j) > 0$ for all existing tasks. Non-college graduates, however, can perform only a subset of tasks. Specifically, there exists $\bar{j} < J$ such that $z_\ell(j) \geq 0$ for tasks in $[0, \bar{j}]$, while $z_\ell(j) = 0$ for tasks $j \geq \bar{j}$. This implies an exogenous upper bound on the set of tasks accessible to workers without higher education: they are unable to perform frontier tasks, such as scientific research.

Tasks are ordered such that the relative productivity of college graduates to non-college graduates is decreasing with the task index j. That is, college graduates have a comparative advantage in the task with a higher j; and vice versa. The market for tasks is perfectly competitive. Unit production cost of task j by worker type i is: $\gamma_i(j) = w_i/z_i(j)$. Therefore, task j is performed by non-college graduates instead of college graduates if:

$$\omega \leq \frac{z_\ell(j)}{z_c(j)}, \tag{3}$$

where ω denotes the relative wage of non-college graduates to college graduates (w_ℓ/w_c). This condition implies a task assignment rule: lower j tasks are taken by non-college graduates and higher ones are performed by college graduates. The price of each task is given by $\gamma(j) \equiv \min\{\gamma_c(j),\ \gamma_\ell(j)\}$.

Manufacturing Firms A representative firm producing goods combines tasks in the interval $[0, 1]$. This fixed interval of tasks in the production of homogeneous goods is intuitive for traditional goods, which require a fixed set of tasks that always exist. The production technology is Cobb-Douglas, and to produce one unit of manufacturing goods, a firm's expenditure on a specific task j in $[0, 1]$ is given by $\beta(j) \in (0, 1)$. For future reference, we also define the cumulative expenditure share by $\overline{\beta}(j) = \int_0^j \beta(j')dj'$.

Service Firms There are competitive firms for services. They use different tasks over $[0, J]$ as input for production. Given the set of tasks used for service production, their production technology is:

$$y = J^{\tilde{\nu}+\frac{1}{1-\varepsilon}-1} \left[\int_0^J \tau(j)^{\frac{\varepsilon-1}{\varepsilon}} dj\right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{4}$$

where $\tau(j)$ refers to input of task j. The production technology exhibits three features. First, the elasticity of substitution between tasks in the production of services is governed by ε, and we assume that $\varepsilon \in (0, 1)$: tasks are complementary in production. Second, the production of a service requires all tasks between task indexed 0 to J. Intuitively, an asset management firm in the service sector requires both simple tasks (e.g., cleaning, driving) and more skill-intensive ones (e.g., market analysis, fund management). Third, the term $J^{\tilde{\nu}+\frac{1}{1-\varepsilon}-1}$ captures the elasticity of output with respect to the number of tasks. The specification follows Benassy (1998), and output of services increases given the inputs of each task if $\tilde{\nu} > 0$. To see this, suppose that $\tau(j) = \bar{\tau}$ for all tasks. Then, the output of services is: $y = J^{\tilde{\nu}}\bar{\tau}$. Therefore, the positive parameter $\tilde{\nu}$ reflects the love of variety in the production technology.

The markets for tasks and services are perfect competition, and given the marginal cost of each task $\gamma(j)$, profit maximization implies that the price of the service is:

$$p = \frac{1}{J^{\nu}} \left[\int_0^J \gamma(j)^{1-\varepsilon} dj\right]^{\frac{1}{1-\varepsilon}}, \tag{5}$$

where $\nu \equiv \tilde{\nu} + \frac{1}{1-\varepsilon} - 1$. The expenditure share of service firms on different task j in production is:

$$\theta(j) = \frac{\gamma(j)^{1-\varepsilon}}{\int_0^J \gamma(j')^{1-\varepsilon} dj'} \tag{6}$$

4.2 Equilibrium

The labor market clearing condition states that labor supply and demand are equal for each type i. Combining the two equations for the two types of labor, we derive the labor market clearing

condition in terms of the relative wages of non-college graduates to college graduates:

$$\omega^* = \frac{(1-\alpha)\overline{\beta}(j^*) + \alpha \int_0^{j^*} \theta(\tau)\, d\tau}{(1-\alpha)\left[1-\overline{\beta}(j^*)\right] + \alpha \int_{j^*}^{J} \theta(\tau)\, d\tau} \frac{L_c}{L_\ell} \equiv \Gamma\left(j^*, \frac{L_c}{L_\ell}, J\right), \tag{7}$$

where, α denotes the income share on services; and $\theta(\tau)$ is the input share of task $\tau \in [0, J]$ in the production of services. Derivation of equation (7) is relegated to Appendix A.2. We now formally define the equilibrium for this economy.

Definition 1. *Given the mass of non-college graduates* (L_ℓ) *and college graduates* (L_c)*, the equilibrium is characterized by the wage ratio of non-college to college graduates* ω^* *and task assignment* j^* *that solves condition* (3) *with equality, and labor market cleaning condition* (7)*.*

Figure 5 illustrates the competitive equilibrium. The wage curve $\Gamma(j, L_c/L_\ell, J)$ is increasing in task index j and $\lim_{j\to\infty} \Gamma(j, \frac{L_c}{L_\ell}, J) = \infty$. Since the right-hand side of the relative labor productivity of non-college to college graduates in condition (3) is decreasing in j, the threshold of task index j^* and wage ratio ω^* are uniquely determined in equilibrium.

Proposition 1. *Given the mass of non-college graduates* (L_ℓ) *and college graduates* (L_c)*, we have a unique equilibrium* (j^*, ω^*)*. Tasks indexed by* $[0, j^*]$ *are performed by workers; and those indexed by* $[j^*, J]$ *are performed by college graduates.*

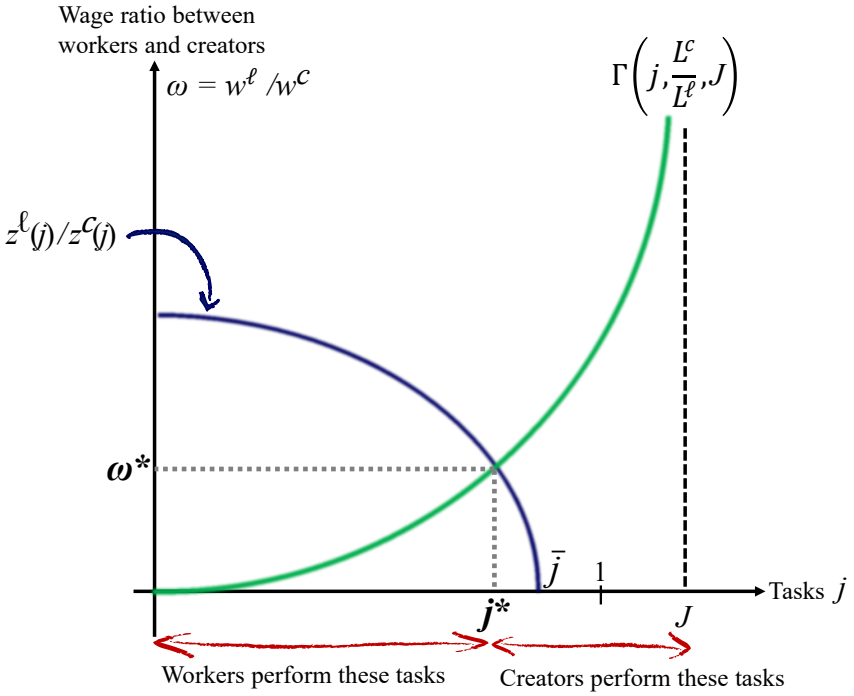
4.3 Comparative Statics: Race Between Education and Technology

Our model can be used to study the effects of labor supply, task dissemination and innovation on the local labor market, which are linked to the various roles of a university. To begin with, education increases the number of college graduates relative to non-college graduates, therefore larger L_c/L_ℓ. *Ceteris paribus*, a stronger supply of college graduates results in a higher relative wage between non-college and college graduates because of an upward shift of the wage curve: $\Gamma(j, k\frac{L_c}{L_\ell}, J) > \Gamma(j, \frac{L_c}{L_\ell}, J)$ for any constant $k > 1$ and task j. This results in a lower threshold of task j^* and higher ω^*, as illustrated in Panel (a) of Figure 6. Therefore, we have *downgrading* of tasks for creators together with *lower* skill premium.

Next, we explore the impact of innovation that introduces new tasks to the local labor market, another role of universities suggested by the data findings. Our model captures the emergence of new tasks by a rightward shift in J. While this does not alter the relative productivity of non-college graduates, it does cause a shift in the wage curve. Suppose that the wage curve shows:

$$\Gamma\left(j, \frac{L_c}{L_\ell}, J\right) > \Gamma\left(j, \frac{L_c}{L_\ell}, J + \Delta\right), \quad \forall\, j \in [0, J] \tag{8}$$

Figure 5: Equilibrium Illustration



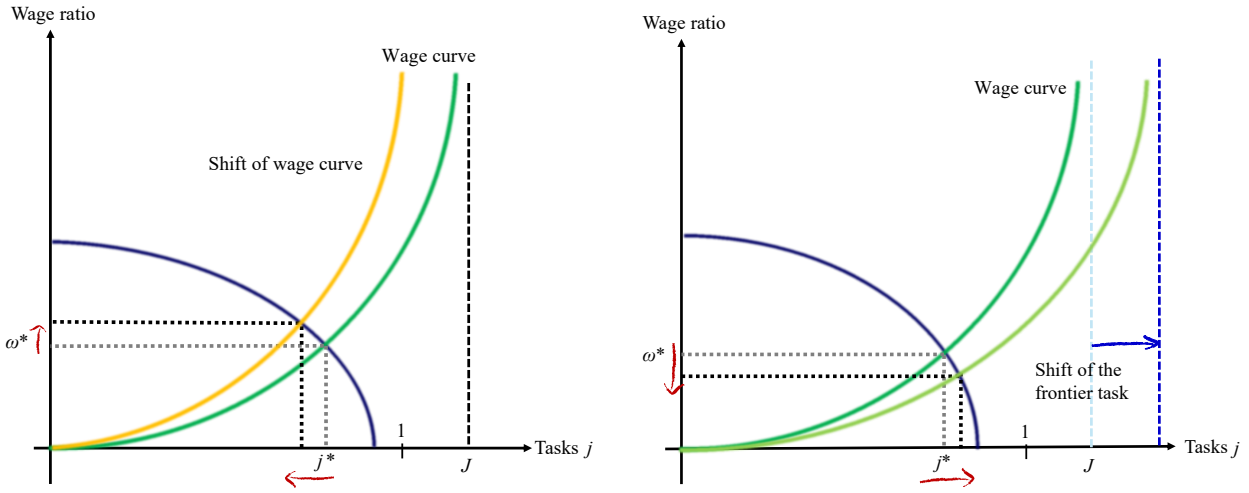
where new tasks expand the set of tasks from J to $J+\Delta$. By assumption, the newly created tasks are performed by college graduates, who have comparative advantages in doing so, and the production of services using those new tasks disproportionately increases the demand for relatively complex tasks (an increase in the denominator of equation (7)). Panel (b) of Figure 6 shows the labor market effect of this *skill-biased innovation in tasks*. As a result, the equilibrium wage ratio ω^* falls: an increase in demand for college graduates results in a higher skill premium. In addition, the set of tasks performed by non-college graduates $[0, j^*]$ expands with college graduates specializing in more complicated tasks.

Our model can also be used to study the impact on the local labor market if the relative productivity $\frac{z_\ell(j)}{z_c(j)}$ changes. Non-college graduates can adopt new technology that expands the set of tasks available to them, captured by an increase in $\bar{j}$. This implies that non-college graduates become able to perform tasks for which college graduates have relatively high productivity. This dissemination process increases the relative productivity of non-college graduates performing tasks of higher index. In equilibrium, it leads to a higher relative wage ω^* and an expansion of the set of tasks $[0, j^*]$ that non-college graduates perform.

The following proposition summarizes these effects:

Proposition 2. *(i) If the ratio of college graduates to non-college graduates (L_c/L_ℓ) increases, the wage ratio ω^* increases and set of tasks by non-college graduates $[0, j^*]$ shrinks; (ii) If there is skill-biased innovation in tasks that expand the set of tasks from $[0, J]$ to $[0, J+\Delta]$ with (8), the wage*

Figure 6: Supply of High-skilled Labor and Innovation of Tasks



(a) Supply of High-skills **(b)** Innovation

ratio ω^* *decreases and the set of tasks performed by non-college graduates* $[0, j^*]$ *expands; and* (iii) *If dissemination of technology is accompanied by an increase in* $\bar{j}$*, the wage ratio* ω^* *increases and the set of tasks perfomed by non-college graduates* $[0, j^*]$ *expands.*

A formal proof of this proposition is provided in Appendix A.3. Together, the race between education, task dissemination, and task innovation may have an ambiguous impact on the wage ratio and the set of tasks performed by non-college and college graduates. Yet, each of the three channels indicates a distinct response from the local labor market. In what follows, we focus on the case in which innovation of creating new tasks is skill-biased and satisfies (8), given the number of non-college and college grduates.

4.4 The Rise of Services

We now use the model to illustrate how and why services grow in the local economy. Specifically, we examine the labor used in services and discuss how it's driven by different factors.[12] The mass of labor inputs in the service sector equals the mass of workers and creators producing tasks used for the service sector, namely,

$$E_{\text{Service}}\left(\omega^*, j^*;\ J\right) = \underbrace{(1-\omega^*)\left(\int_0^{j^*} \frac{1}{z^{\ell}(j)}dj\right) D_{\text{Service}}}_{\substack{\text{Labor demand for workers} \\ \text{performing tasks for services}}} + \underbrace{\omega^* p(J) D_{\text{Service}}}_{\substack{\text{Labor demand for creators} \\ \text{performing tasks for services}}}, \tag{9}$$

where D_{Service} is the aggregate demand of services.

[12]Given the total number of creators and workers is fixed, an increase in labor for services implies a higher employment share for services.

The first term represents the demand for workers who perform tasks over $[0, j^*]$, which is employed by service firms that produce services indexed by $j \in [1, J]$. The labor demand for workers increases as their relative compensation becomes more cost-effective to perform the same task when the wage ratio ω decreases. The second term captures the demand for creators in the production of services, which increases when the wage of creators (w^c) is low given the production cost of the frontier services $p(J)$. Then, we obtain the following proposition:

Proposition 3. *Given demand, task reallocation from creators to workers associated with lower wage ratio ω leads to an increase in the employment share of services.*

The proof is relegated to Appendix A.3. The intuition of Proposition 3 is as follows. First, the demand for workers who perform tasks used in services increases. Second, the input costs of all service firms, including frontier service, decrease as a result of the increased number of tasks performed by workers, given the set of services and wages. The relative effect of them is determined by the level of relative wages (ω), so overall employment in services increases if the wage ratio is sufficiently small.

Now consider the effects of an innovation that increases the frontier of the tasks (J), given the demand schedule for services D_{Service}. An increase in J impacts service jobs in four ways: first, advancing the frontier lowers relative wages and reallocates tasks from creators to workers; second, it hinges on whether workers doing new tasks are assigned to services or manufacturing; third, innovation results in the emergence of new firms that provide new services, thereby increasing the need for tasks involved in their production; fourth, the cost associated with producing new services changes compared to the creator's wage, affecting the demand for creators.

Among the four channels above, the first three are associated with an increase in service employment, and the last effect is non-negative if an increase in the production cost of the frontier service $p(J)$ dominates an increase of wage premium $(1/\omega)$, namely, $\omega_1^* p(J_1) > \omega_0^* p(J_0)$ for $J_0 < J_1$. Then the demand for creators who perform tasks intensively used in the frontier services increases. This effect relies on the shape of creators' productivity. We summarize the results in the following Proposition 4:

Proposition 4. *Given the demand schedule, the introduction of new tasks into the frontier from J_0 to J_1 increases the employment share of services when the production cost of the frontier service $p(J)$ increases more than wage premium: $\frac{p(J_1)}{p(J_0)} \geq \frac{1/\omega_1^*}{1/\omega_0^*}$. The effects are more pronounced if demand for the frontier service increases and more tasks are reallocated from creators to workers.*

We also show that creating new tasks results in an increase in the within-sector labor composition. In particular, more workers work in the manufacturing sector, while more creators work in the service sector. This effect is independent of the change in prices of services but depends on the rightward shift of the threshold j^* and decrease in wage ratio ω^*.

Proposition 5. *The introduction of new tasks at the frontier increases the share of workers in the manufacturing sector and the share of creators in the service sector.*

Taken together, these results show that the innovation of new tasks can be an important factor underlying the rise of the services and the decline of the manufacturing sector. It is associated with a skill-biased shift within the service sector through the task reallocation as well as a higher skill premium.[13] We now turn to discuss the implications of universities in the process.

4.5 The Roles of Universities: Linking Theory with Empirical Facts

Based on Propositions 2 to 4, we derive the theoretical implications of a university presence on the rate of structural transformation and relate them to the facts documented in Section 3.

First, universities are the hubs of talent, which supply high-skilled individuals with college degrees. Following Proposition 2 (i), this force should have led to a lower wage premium for creators. By contrast, the college wage premium has increased over time, especially in regions with colleges, as evidenced by Fact 3 in Section 3. In addition, an increase in the supply of creators results in the reallocation of tasks from workers to creators, i.e., smaller j^*. By equation (9), a reduction in wage premium and reallocation of tasks from workers to creators is associated with lower employment share of services *ceteris paribus*, which suggests that overall, this channel cannot be the dominant force in accounting for the empirical observations documented in Section 3.

Second, universities are the hubs of technological progress in the local economy. Following Proposition 2 (ii) and (iii), when low-skilled individuals adopt new technology to perform relatively complex tasks, and high-skilled individuals need to perform new tasks developed with innovation, they reallocate tasks previously performed by high-skilled (creators) to low-skilled (workers). Furthermore, this task reallocation increases the share of labor inputs in the service sector, accompanied by a high wage premium and a high price of frontier services, as in Proposition 3 and 4. We also confirm that an innovation of adding new tasks must lead to a larger share of high-skilled workers in the service sector, as in Proposition 5. This is consistent with a significant employment growth of high-skill services illustrated in Figure 2.

Third, the relative magnitude of task dissemination and invention determines the direction of the wage premium change (Figure 6). Fact 4 in Section 3 highlights that new tasks predominantly emerge in regions with a university. If innovation is sufficiently strong to create enough new tasks, the wage premium for creators will increase, as in Proposition 3. Together, our theory highlights the importance of universities as innovation hubs, which increase both wage premium and employment in services.

[13] In Appendix A.4 we present analytical results using a simple parametrization of productivity.

4.6 Discussion: Sources of Structural Transformation

To situate the mechanisms in our theory within the broader literature, it is useful to clarify how they relate to, and differ from, existing explanations of structural transformation.

Income effects A key mechanism emphasized in this literature is income effects (e.g., Buera and Kaboski, 2012; Comin, Lashkari, and Mestieri, 2021). In our model, the expenditure share on the service sector is fixed; therefore, there are no income effects. Nonetheless, our model can be easily extended to accommodate non-homothetic preferences. In such an extension, an increase in the wages of creators results in a high expenditure share on the service sector, which in turn drives further demand for tasks that are used for services, which magnifies the mechanisms emphasized in Section 4.4.

Relative price effects Another key mechanism explaining structural transformation is relative price effects: the development of the economy is associated with an increase in the price of services relative to other goods. This effect also exists in our model. As the set of tasks expands, the relative price of new services to goods rises since (i) the relative wage of creators intensively used in new services increases; and (ii) the manufacturing goods price declines as the proportion of workers in production of the manufacturing sector grows. Therefore, we observe such relative price changes along with the structural transformation.

Sectoral productivity In the literature, the relative sectoral productivity growth is often highlighted as a key factor in explaining structural transformation. For example, in Buera et al. (2022), sector-specific productivity growth is an important source of the skill-biased structural change and skill premium. Despite that we abstract from exogenous sectoral productivity, in Appendix A.5, we show that the measure of the endogenous total factor productivity of the manufacturing sector in the model grows if (i) the labor productivity of workers $z^{\ell}(j)$ increases and the task is allocated more to workers (i.e., an increase in j^*); or (ii) the labor productivity of creators $z^{c}(j)$ increases and the task is allocated more to creators (i.e., a decrease in j^*). The first case involves the dissemination of tasks, as illustrated in Section 4.3, while the second case relates to the skill-biased technical change, in which education can disproportionately improve the productivity of creators. Taken together, our theory provides a micro-foundation for both (relative) sectoral productivity growth and skill-biased technical change.

5 Quantitative Model

In this section, we extend the model developed previously to quantify the role of universities and to decompose the drivers of local growth of high-skill services.[14] We proceed in three steps. First, we present a quantifiable version of our theory in an economy comprising multiple regions and two sectors: the low-skill and the high-skill sectors. Our definition of a low-skill intensive sector includes traditional manufacturing industries and low-skill services, such as retail. Therefore, we use manufacturing to refer to the low-skill-intensive sector for simplicity. On the other hand, the high-skilled-intensive sector mostly consists of high-skill services, and we use high-skill services to refer to the high-skill-intensive sector. Second, we define the general equilibrium and derive an equilibrium relationship that links the growth of high-skill services and the wage premium for college graduates. Lastly, we use these equations to isolate the distinct theoretical channels that account for variation in service growth and wage premiums across locations.

The economy consists of N discrete locations; let $\mathcal{R}$ refer to the set of locations. Each location is indexed by subscripts $n, n' \in \mathcal{R}$, which corresponds to each CZ in our empirical analysis. There are two sectors indexed by superscripts $k \in \{M, S\}$: Manufacturing (M), and High-skill services (S). As in the simple model, there are two types of individuals $i \in \{\ell, c\}$: non-college graduate (ℓ) and college graduate (c). Total mass of college graduates in a country is exogenous and given by: $\bar{L}_c = \sum_{n \in \mathcal{R}} L_{cn}$. Individuals supply one unit of labor to engage in a task, as in Section 4. To examine the long-run impact of universities, our baseline specification considers the mobility of college graduates' location decisions.[15] We allow locations to differ in sectoral productivity and residential floor space supply.

5.1 Preferences

We assume a nested preference structure, in which preferences are first defined over housing and consumption across two sectors, and then over manufacturing and high-skill services. In the upper tier, we assume Cobb-Douglas utility with constant housing expenditure share $1 - \mu_i$ for each type i.[16] For the lower tier of utility, we assume for simplicity a CES functional form over two sectors with elasticity of substitution α. Within the manufacturing sector, we posit a CES functional form over differentiated goods with elasticity of substitution β. Namely, the utility of

[14] See Appendix B for the derivation of all theoretical results presented in this section.

[15] In the US, university graduates are more mobile across locations, and the direct effect of their supply on the local labor market is not necessarily large. Instead, these high-skilled individuals tend to gravitate towards locations that offer a wider range of services. Therefore, we introduce mobility of college graduates in the economy along with different housing prices across locations, which are determined in the local housing market.

[16] Type-specific expenditure shares on residential floor spaces follow the recent literature on spatial sorting.

type i who resides in region n is:

$$u_{in} = b_n \left[\frac{1}{\mu_i} \left({\varphi^M}^{\frac{\alpha-1}{\alpha}} \left(\left(\sum_{n' \in \mathcal{R}} {q^M_{inn'}}^{\frac{\beta-1}{\beta}} \right)^{\frac{\beta}{\beta-1}} \right)^{\frac{\alpha-1}{\alpha}} + {\varphi^S}^{\frac{\alpha-1}{\alpha}} {q^S_{in}}^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\alpha}{\alpha-1}} \right]^{\mu_i} \left[\frac{h_{in}}{1-\mu_i} \right]^{1-\mu_i}, \tag{10}$$

where b_n refer to the utility benefit from amenities; φ^k captures the relative weight of each sector in consumer utility; $q^M_{inn'}$ is consumption of manufactuing goods produced in region n'; q^S_{in} is consumption of servcies; and h_{in} refer to residential floor space consumption. Following the literature of structural transformation in macroeconomics, we assume $0 < \alpha < 1$.

Manufacturing goods are differentiated by production place and freely traded across regions. Individuals consume the differentiated manufacturing goods. Under the CES functional form, the expenditure share of manufacturing goods produced in n and the price index of the manufacturing sector are:

$$\pi_n = \frac{{p^M_n}^{1-\beta}}{\sum_{n' \in \mathcal{R}} {p^M_{n'}}^{1-\beta}}, \quad P_M = \left[\sum_{n \in \mathcal{R}} \left(p^M_n \right)^{1-\beta} \right]^{\frac{1}{1-\beta}}, \tag{11}$$

where p^M_n is the price of manufacturing goods produced in n, and the price index of the manufacturing sector is identical across regions. The expenditure minimization problem leads to the price index of consumption across two sectors given by:

$$\mathbb{P}_n = \left[\left(P^M / \varphi^M \right)^{1-\alpha} + \left(P^S_n / \varphi^S \right)^{1-\alpha} \right]^{\frac{1}{1-\alpha}}, \tag{12}$$

where P^S_n refers to price of high-skill services. We assume that high-skill services are non-tradable.[17]

The indirect utility of individuals of type $i \in \{\ell, c\}$ in region n becomes:

$$\mathbb{V}_{in} = \frac{b_n w_{in}}{(\mathbb{P}_n)^{\mu_i} (r_n)^{1-\mu_i}}, \tag{13}$$

where w_{in} is the wage of type i in location n, and r_n is the price of residential floor space. There are agglomeration and congestion forces in our model coming from preferences. First, when the larger task set lowers the price index of high-skill services, this implies higher real income. Second, consumption of residential floor space creates a dispersion force through floor space prices. There are competitive developers who supply residential floor spaces in each region n: $H_n = G_n {r_n}^{\kappa}$, where κ is the housing supply elasticity and G_n is the productivity of developers in region n.

[17] We relax this assumption later XXX

5.2 Tasks

Each task is produced by college or non-college graduates, as in Section 4. Given the wages of non-college graduates ($w_{\ell n}$) and college graduates (w_{cn}) and their productivity $z_i(j)$ for tasks j, cost minimization leads to the cost of each task j in region n satisfying:

$$\gamma_n(j) = \min\left\{\frac{w_{\ell n}}{a_{\ell n} z_\ell(j)}, \frac{w_{cn}}{a_{cn} z_c(j)}\right\}, \tag{14}$$

where $a_{\ell n}$ and a_{cn} are task-neutral productivity of non-college and college graduates in n. Let $\omega_n \equiv w_{\ell n}/w_{cn}$ refer to the wage ratio of non-college graduates to college graduates in n, the condition (14) holds with equality for the task j^* above which college graduates perform tasks. Namely,

$$\omega_n = \frac{a_{\ell n}}{a_{cn}} \frac{z_\ell(j_n^*)}{z_c(j_n^*)} \tag{15}$$

for such task j_n^*. The task j_n^* is the highest task performed by workers in region n.

5.3 Production

Manufacturing Manufacturing goods are differentiated by region and tradable. Manufacturing firms in each region use the fixed set of tasks $j \in [0,1]$ to produce manufacturing goods.[18] Production technology is a CES aggregate of a continuum of tasks with elasticity of substitution σ, and the task-neutral productivity in the manufacturing sector in location n is A_n^M. Markets are assumed to be perfectly competitive. Profit maximization and zero profits lead to the price of manufacturing goods produced in n:

$$p_n^M = \frac{1}{A_n^M}\left[\int_0^1 \gamma_n(j)^{1-\sigma} dj\right]^{\frac{1}{1-\sigma}}, \tag{16}$$

where the price of manufacturing goods in region n is low when the region has higher task-neutral productivity (A_n^M) and lower costs of fixed-set of tasks, $\gamma_n(j)$.

High-Skill Services Next, we consider high-skill services. Firms in region n in the high-skill service sector use the continuum of tasks $j \in [0, J_n]$ available in that region. As in the simple theory in Section 4, we assume that their production technology is:

$$y_n^S = A_n^S J_n^{\tilde{\nu}+\frac{1}{\varepsilon-1}-1}\left[\int_0^{J_n} \tau_n(j)^{\frac{\varepsilon-1}{\varepsilon}} dj\right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{17}$$

where A_n^S is the task-neutral productivity of high-skill services. Profit maximization leads to the unit cost of serving a high-skill service in n:

$$p_n^S = \frac{J_n^{-\nu}}{A_n^S}\left[\int_0^{J_n} \gamma_n(j)^{1-\varepsilon} dj\right]^{\frac{1}{1-\varepsilon}}, \tag{18}$$

[18] We consider manufacturing firms include producers of low-skill services.

where $\nu \equiv \tilde{\nu} + \frac{1}{1-\varepsilon} - 1$. The price of high-skilled services in region n depends on task-neutral productivity of high-skill services (A_n^S), the set of tasks (J_n) and the cost of each tasks $(\gamma_n(j))$.

Importantly, the change in the frontier task, J_n, affects the high-skill services via three channels. First, given the price of tasks, increasing the number of tasks required in production leads to a higher production cost when tasks are complementary. To see this, suppose that $\nu = 0$ and let $\bar{\gamma}_n$ denote the average price of tasks in region n. Then, the price of high-skill services is $p_n^S = \bar{\gamma}_n J_n^{\frac{1}{1-\varepsilon}} / A_n^S$, which is increasing in J_n when $\varepsilon < 1$. Second, introducing new tasks reallocates a set of intermediate-level tasks from college graduates to non-college graduates, thereby reducing labor costs in production. Third, an increasing number of tasks in production reduces the production cost when $\nu > 0$. Intuitively, adopting more tasks requires firms to be highly productive. Therefore, the unit cost of producing high-skilled services declines when firms use more tasks. Lastly, the services are not tradable, so we have $P_n^S = p_n^S$ for all regions.

[XXX add discussion of diffusion of technology based on Kalyani et al. (2025)]

5.4 Universities and New Tasks

There are potentially a large number of tasks in the economy, and regions differ in the set of tasks adopted by high-skill service firms, J_n, in equilibrium. We consider the two roles of universities in the creation and adoption of new tasks through research activities in the local economy.

First, regions with stronger university presence create more frontier tasks since, with universities, more research activities may lead to innovative new jobs. Second, firms adopt more frontier tasks in their production when universities exist. Intuitively, the presence of universities lowers the adoption costs of new tasks for high-skill service firms through collaborative activities between the firms and universities in the local economy. Both larger extent of innovation and adoption of new tasks due to the presence of universities expand the set of available tasks used in high-skill services. In a nutshell, we can consider the following specification for the link between universities and the new tasks:

$$J_n = F(A_n^R, \mathcal{U}_n), \tag{19}$$

where the function is increasing in the fundamental productivity of innovation, A_n^R, and increasing in the local university, captured by the level of $\mathcal{U}_n$. The function may indicate log supermodularity between the two elements, as university and fundamental productivity are complementary in task creation and adoption.

By expanding J_n, universities induce a skill-biased deepening of high-skill services. Since frontier tasks are performed by college graduates, widening J_n therefore raises relative demand for high-skilled labor and, through general equilibrium, the skill premium. The mechanism aligns with stylized facts in Section 3. Regions with universities exhibit higher concentrations of occu-

pations with many new titles (Fact #3); faster growth of high-skill services (Fact #1); and larger increases in the skill premium (Fact #2).

Our formulation speaks to anecdotal evidence in the US. In Silicon Valley, Stanford-linked Very Large-Scale Integration (VLSI), Computer-Aided Design (CAD) and UNIX networking tasks diffused into financial and enterprise services (for example, risk analytics, distributed systems). In Pittsburgh, Carnegie Mellon's Robotics Institute catalyzed computer vision and automation tasks that later scaled into industrial services and healthcare applications. In each case, university research labs lowered adoption cost through co-located talent, prototyping facilities, and IP transfer, which moved the local frontier J_n out and raised the demand for high-skill services.[19]

5.5 Market Clearing

College graduates (c) are freely mobile across regions, while non-college graduates (ℓ) are not able to move. Given the indirect utility (13), the free mobility of college graduates implies that their indirect utility $(\mathbb{V}_{cn})$ is equalized across regions for college graduates:

$$\mathbb{V}_{cn} = \frac{b_n w_{cn}}{\left(\mathbb{P}_n\right)^{\mu_c}\left(r_n\right)^{1-\mu_c}} = \bar{v}_c, \quad \forall\, n = 1, 2, \cdots, N \tag{20}$$

where $\bar{v}_c$ is the utility level for college graduates in the economy.[20] Intuitively, housing prices rise in tandem with wage growth and the influx of college graduates to a location, acting as a dispersion force in the economy.

Goods market clearing conditions for the manufacturing sector imply that demand for manufacturing goods produced in region n is:

$$X_n^M = \pi_n \left(\varphi^M\right)^{-(1-\alpha)} \left(P^M\right)^{1-\alpha} \sum_{i\in\{\ell,c\}} \sum_{n'\in\mathcal{R}} \mathbb{P}_{n'}^{-(1-\alpha)} \mu_i w_{in'} L_{in'} \tag{21}$$

For high-skill services, the market clearing condition requires:

$$X_n^S = \left(\varphi^S\right)^{-(1-\alpha)} \left(P_n^S\right)^{1-\alpha} \mathbb{P}_n^{-(1-\alpha)} \sum_{i\in\{\ell,c\}} \mu_i w_{in} L_{in}, \tag{22}$$

Labor market clearing condition for non-college graduates in each region requires that the total payment for non-college graduates $(w_{\ell n} L_{\ell n})$ equals the sum of payments to workers in the production of tasks used in manufacturing and high-skill services:

$$w_{\ell n} L_{\ell n} = \int_0^{j_n^*} \frac{\gamma_n(j)^{1-\sigma}}{\int_0^1 \gamma_i(j')^{1-\sigma} dj'} X_n^M dj + \int_0^{j_i^*} \frac{\gamma_n(j)^{1-\varepsilon}}{\int_0^{J_n} \gamma_n(j')^{1-\varepsilon} dj'} X_n^S dj, \tag{23}$$

[19] These examples are consistent with well-documented university spillovers into local innovation (for example, Valero and Van Reenen 2019; Moretti 2021; Hausman 2022; Bergeaud et al. 2025).

[20] Note that Equation (20) holds with inequality if $L_{cn} = 0$. In the following discussion, we suppose that all regions have a positive number of college graduates so that equation (20) holds for all regions.

Analogously, the labor market clearing condition for college graduates in region n is:

$$w_{cn}L_{cn} = \int_{j_i^*}^{1} \frac{\gamma_n(j)^{1-\sigma}}{\int_0^1 \gamma_n(j')^{1-\sigma}dj'} Y_n^M dj + \int_{j_i^*}^{J_n} \frac{\gamma_n(j)^{1-\varepsilon}}{\int_0^{J_n} \gamma_n(j')^{1-\varepsilon}dj'} Y_n^S dj, \tag{24}$$

where the right-hand side combines the payments to college graduates performing tasks used in the manufacturing sector (first term) and high-skill services (second term).

Lastly, residential floor space market cleaning implies floor space price in region n is given by:

$$r_n = \frac{1}{H_n} \sum_{i \in \{\ell, c\}} (1 - \mu_i) w_{in} L_{in} \tag{25}$$

5.6 General Equilibrium

The equilibrium distribution of economic activities across locations is determined by (i) the set of parameters in preference and technology (α, μ_c, μ_ℓ, φ^k, β, σ, ε); (ii) the task performance of college graduates and non-college graduates in the aggregate economy $z_c(j)$ and $z_\ell(j)$; and (iii) the heterogeneity across regions in the mass of workers $\{L_{\ell n}\}$, universities $\{\mathcal{U}_n\}$, task-neutral productivity $\{A_n^k\}$, productivity of developers $\{G_n\}$, amenities $\{b_n\}$, value of creating new tasks q and total number of college graduates in the country, $\bar{L}_c$. We now define the equilibrium for this multi-region economy.

Definition 2. *Given the exogenous variables of the model and economy-wide parameters, the equilibrium is characterized by the following endogenous variables: wages of non-college and college graduates $\{w_{in}\}$, the distribution of college graduates $\{L_{cn}\}$, the task assignment $\{j_n^*\}$, the frontier of tasks $\{J_n\}$, floor space prices $\{r_n\}$ and common real income $(\bar{v}_c)$ such that (i) task assigned non-college and college graduates to minimize the cost* (14)*; (ii) goods and labor market clear* (21)*–*(24)*; (iii) firms adopt tasks satisfying* (19)*; (iv) profit maximization and zero profits of developers and housing market clear* (25)*; and (v) free mobility condition for college graduates* (20)*.*

We present the details of equilibrium conditions and model solutions in Appendix B.1. We use the quantitative model to evaluate the implication of the existence of universities in the local economy for the spatial distribution of college graduates and employment of services through different channels.

Let us consider a region n with highly ranked universities, where the university parameter $(\mathcal{U}_n)$ is large. Suppose there is a positive shock on innovation of new tasks, A_n^R. First, a region with a university can expand the task set, J_n, more than other regions. Creation of new tasks raises the relative wage of college graduates compared to non-college graduates (college premium), $1/\omega_n$, as shown in Proposition 2.

Second, introducing new tasks triggers the reallocation of tasks from college graduates to non-college graduates, captured by the shift of the threshold, j_n^*. When the college premium is sufficiently large, the shift leads to lower price of high-skill services in the region. Combined with higher relative wages, this increases the real income of college graduates, $\mathbb{V}_{cn}$, attracting more college graduates from other regions.

Third, inflow of college graduates increases the employment share of the high-skill service sector, since they tend to produce tasks that are intensively used in high-skill services. Moreover, the production of such services requires a broad array of tasks, thereby increasing the share of both non-college and college graduates engaged in service-related activities. As discussed in Section 4.4, these dynamics disproportionately raise the labor share in services.

Fourth, a larger number of college graduates, L_{cn}, leads to higher residential floor space prices. Therefore, this process continues until the housing price, r_n, reaches a sufficiently high level, leading to the dispersion of college graduates to different regions.

These mechanisms are at work for other types of positive shocks, including a shock to the productivity of the manufacturing sector. In a nutshell, differences in the level of universities across regions lead to different spatial patterns of wage premium and structural transformation, taking labor away from manufacturing to services due to a *positive feedback loop* between task creation and rising demand for high-skill services and college graduates. We quantitatively evaluate the importance of this channel in the next section.

6 Quantification

6.1 Model Parameters

Table 2 summarizes the economy-wide parameters and assigned values in our calibration. We set the elasticity of substitution between tasks in the production of the manufacturing sector, σ, equal to 0.5. We also assign the same value for the elasticity of substitution between tasks in the production of high-skill services.

There are other parameters we need to assign. First, we set the expenditure share on residential floor space such that $1 - \mu_c = 0.15$ for college graduates and $1 - \mu_\ell = 0.25$ for non-college graduates following Diamond and Moretti (2024). Second, the elasticity of substitution between manufacturing and high-skill services in consumption, α, is set to 0.5, following the standard value in the macroeconomic literature on structural transformation. Third, among the manufacturing goods, the elasticity of substitution between goods produced by different regions, β, is set to 4, which is in the middle of the estimates of trade literature. Lastly, we assign the floor space supply elasticity, κ, by 1.75 based on the estimates of Saiz (2010) for the U.S. cities.

Table 2: Parameter values and sources

Parameter	Notation	Value	Source
Elasticity of substitution between tasks			
— in manufacturing	σ	0.5	
— in high-skill services	ε	0.5	
Expenditure share on residential floor space			
— of college graduates	$1-\mu_c$	0.15	Diamond and Moretti (2024)
— of non-college graduates	$1-\mu_\ell$	0.25	
Elasticity of substitution across sectors	α	0.5	
Floor space supply elasticity	κ	1.75	Saiz (2010)
Elasticity of substitution between manufacturing goods	β	4	Trade literature

Note: This table summarizes the parameter values in the model. The first column lists each parameter; the second column contains the corresponding notation; the third column gives its calibrated value; and the fourth column summarizes the source for the calibrated value.

We posit the following parameterization of productivity in performing tasks:

$$\begin{aligned} z_{\ell t}(j) &= \Omega_{\ell t} e^{-\lambda_\ell j}, \\ z_{ct}(j) &= \Omega_{ct} e^{-\lambda_c j} \end{aligned} \tag{26}$$

where the scale parameters $(\Omega_{\ell t}, \Omega_{ct})$ capture absolute advantage in performing tasks for different types of workers; and the shape parameters $(\lambda_c, \lambda_\ell)$ capture the comparative advantage of them. Since college graduates have a comparative advantage for performing higher tasks, we consider that the parameter values satisfy: $\lambda_\ell > \lambda_c$.

6.2 Model Inversion

We next use the observed data and the structure of our model to recover unobserved variables, such as sectoral level productivity, prices, amenities and frontier tasks, which are inputs into our counterfactuals below. We explain the model inversion in order. We present the details in Appendix C.

First, we exploit market clearing conditions (21) and (22) to obtain sectoral prices. Conditional on the data on wages of non-college and college graduates $\{w_{int}\}$, employment by sector $\{L^M_{int}, L^S_{int}\}$ and parameters (μ_i, α, β), we solve N equations of high-skill services market clearing condition for the adjusted prices for high-skilled services $(\widetilde{P}^S_{nt} \equiv P^S_{nt}/\varphi^S_t)$ and N equations of the market clearing condition for manufacturing goods for adjusted productivity of manufacturing sector $(\widetilde{A}^M_{nt} \equiv \varphi^M_t A^M_{nt})$. Using the adjusted prices, we compute the aggregate price index, $\mathbb{P}_{nt}$, across regions.

Second, we solve the labor market clearing condition for non-college and college graduates in each sector conditional on the observed wages $(w_{cnt}, w_{\ell nt})$ and employment distribution $(L^M_{cnt}, L^M_{\ell nt}, L^S_{cnt}, L^S_{\ell nt})$ and inverted prices for the unobserved workers' productivity of college

and non-college graduates $(\widetilde{a}_{cnt}, \widetilde{a}_{\ell nt})$, the task threshold, j^*_{nt}, and the frontier of tasks, J_{nt}, given parameters in task performance $(\lambda_\ell, \lambda_c)$ and elasticity of substitution between tasks (σ, ϵ).

In this step, we also estimate the key parameters in the model, $(\lambda_\ell, \lambda_c)$ by using equation (15). Under the parametrization of task performance (26), the equilibrium relationship for the task assignment leads to:

$$\ln\left[\frac{w_{cnt}}{w_{\ell nt}}\right] = \ln\left[\frac{\widetilde{a}_{cnt}}{\widetilde{a}_{\ell nt}}\right] + (\lambda_\ell - \lambda_c) j^*_{nt}, \tag{27}$$

This implies that the skill premium captured by the wage ratio between college graduates and non-college graduates $(w_{cnt}/w_{\ell nt})$ in region n is decomposed into the contribution of the difference in the task-neutral productivity between college graduates and non-college graduates $(\widetilde{a}_{cnt}/\widetilde{a}_{\ell nt})$ and the task assignment rule between them, j^*_{nt}. When $\lambda_\ell > \lambda_c$, the rightward shift of the threshold (i.e., increase in j^*_{nt}) leads to an increase in the skill premium. The model inversion described above allows us to obtain the right-hand side in equation (27). Therefore, we estimate the parameters to match their values and observed skill premium in the left-hand side.

Third, we solve zero profit conditions for high-skill services productivity $(\widetilde{A}^S_{nt} \equiv \varphi^S_t A^S_{nt})$ conditional on the inverted prices $(\widetilde{P}^S_{nt})$, backed out task performance $(\widetilde{a}_{\ell nt}, \widetilde{a}_{cnt})$, task threshold (j^*_{nt}) and task frontier (J_{nt}) in the second step. We obtain the unobserved productivity for high-skill services in each region.

Fourth, we use the rest of equilibrium conditions for inversion of location advantages in amenities and developers. The free mobility condition for college graduates implies that indirect utility of college graduates in region n in period t is:

$$\ln \bar{v}_t = \ln w_{cnt} + \ln b_{nt} - \mu_c \ln \mathbb{P}_{nt} - (1-\mu_c) \ln r_{nt} \tag{28}$$

Subtracting the average of them and normalize the geometric mean of amenities $(\frac{1}{N}\sum_i \ln b_{nt} = 0)$ to obtain the value of amenities in each region:

$$\ln b_{nt} = -\ln\left[\frac{w^c_{cnt}}{\bar{w}_{ct}}\right] + \mu_c \ln\left[\frac{\mathbb{P}_{nt}}{\bar{\mathbb{P}}_t}\right] + (1-\mu_c)\ln\left[\frac{r_{nt}}{\bar{r}_t}\right], \tag{29}$$

where we define $\mathbb{P}_t \equiv \left(\prod_n \mathbb{P}_{nt}\right)^{1/N}$ and $\bar{r}_t \equiv \left(\prod_n r_{nt}\right)^{1/N}$ for their geometric means. Turing to the floor space development, we solve the floor space market cleaning condition (25) for developers' productivity, G_{nt}, across regions.

7 Accounting for Growth of Services and Wage Premium in US

With these estimates, we are ready to conduct counterfactual analysis to quantify the degree to which universities drive local structural transformation as well as the underlying mechanisms.

In our first exercise, we feed in the average $(L_{cn,2015}, J_{n,2015})$ across regions with universities to each region n without one, with other fundamentals in n being their current values. We then solve the counterfactual $(w_{cn}, w_{\ell n}, L_n^M, L_n^S)$ for 2015. The same procedure is repeated for all n's.

In the second counterfactual exercise, we examine the three channels through which universities contribute to local structural transformation: (i) supply of high-skilled labor, (ii) creation of new tasks, and (iii) the migration of high-skilled labor. Given the distribution of universities, we fix the high-skilled-to-low-skilled ratio in 2015 to their 1980 levels for regions with universities, to quantify (i). Similarly, we restrict the set of tasks (indexed by J_n) in 2015 to their 1980 levels for regions with universities, in order to quantify (ii). Lastly, we consider an economy with the same set of fundamentals but no migration to quantify (iii).

8 Conclusion

Structural transformation in the US economy exhibited an uneven pattern across regions. This paper studies how universities have contributed to the rise of services to explain such variation. We find four novel empirical facts using rich datasets on local labor markets and universities. First, CZs with universities, particularly high-ranked ones, experienced a greater increase in service sector employment and establishments. Second, regional differences in structural transformation are largely explained by structural changes within tasks and skills. Third, CZs with universities have consistently exhibited higher skill premiums for college-educated workers over the past four decades. Finally, new tasks tend to emerge disproportionately in regions with universities.

Motivated by these patterns, we develop a new theory of local structural transformation featuring heterogeneous task distributions across sectors, endogenous skill-task matching, and an endogenous skill premium. In this framework, universities serve a dual role in the local labor market: they supply high-skilled labor and generate new tasks through innovation. Both functions contribute to the transition from manufacturing to services, but they have distinct implications for task allocation and wage outcomes, which allows us to distinguish the relative importance of each role. Our model highlights that the innovation role of universities is particularly critical in jointly explaining the stronger growth of the service sector and the rising skill premium observed in university regions.

Our work contributes to a deeper understanding of the mechanisms behind regional economic divergence in the US. In ongoing research, we aim to quantify the contribution of universities to local structural transformation, with implications for place-based policy, higher education investment, and regional development strategies.

References

Acemoglu, Daron. 2003. "Patterns of Skill Premia." *The Review of Economic Studies* 70 (2):199–230.

Acemoglu, Daron and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, vol. 4. Elsevier, 1043–1171.

Acemoglu, Daron, David Autor, David Dorn, Gordon H Hanson, and Brendan Price. 2016. "Import Competition and the Great US Employment Sag of the 2000s." *Journal of Labor Economics* 34 (S1):S141–S198.

Acemoglu, Daron and Melissa Dell. 2010. "Productivity Differences Between and Within Countries." *American Economic Journal: Macroeconomics* 2 (1):169–188.

Acemoglu, Daron and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review* 108 (6):1488–1542.

———. 2019. "Automation and New Tasks: How Technology Displaces and Reinstates Labor." *Journal of Economic Perspectives* 33 (2):3–30.

———. 2020. "Unpacking Skill Bias: Automation and New Tasks." In *AEA Papers and Proceedings*, vol. 110. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, 356–361.

———. 2022. "Tasks, Automation, and the Rise in US Wage Inequality." *Econometrica* 90 (5):1973–2016.

Akcigit, Ufuk, Jeremy Pearce, and Marta Prato. 2025. "Tapping into Talent: Coupling Education and Innovation Policies for Economic Growth." *Review of Economic Studies* 92 (2):696–736.

Alon, Titan, Damien Capelle, and Kazushige Matsuda. 2022. "University Research and the Market for Higher Education."

Andrews, Michael J. 2023. "How Do Institutions of Higher Education Affect Local Invention? Evidence from the Establishment of US Colleges." *American Economic Journal: Economic Policy* 15 (2):1–41.

Autor, David, Caroline Chin, Anna Salomons, and Bryan Seegmiller. 2024. "New Frontiers: The Origins and Content of New Work, 1940–2018." *The Quarterly Journal of Economics* 139 (3):1399–1465.

Autor, David, David Dorn, and Gordon Hanson. 2019. "When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men." *American Economic Review: Insights* 1 (2):161–78.

Autor, David H. and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5):1553–97.

Autor, David H, Frank Levy, and Richard J Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics* 118 (4):1279–1333.

Babina, Tania, Alex Xi He, Sabrina T Howell, Elisabeth Ruth Perlman, and Joseph Staudt. 2023. "Cutting the Innovation Engine: How Federal Funding Shocks Affect University Patenting, Entrepreneurship, and Publications." *The Quarterly Journal of Economics* 138 (2):895–954.

Barro, R and Xavier Sala-i Martin. 2004. "Economic Growth, 2nd Edition."

Baum-Snow, Nathaniel and Ronni Pavan. 2012. "Understanding the City Size Wage Gap." *The Review of Economic Studies* 79 (1):88–127.

Baumol, William J. 1967. "Macroeconomics of Unbalanced Growth: the Anatomy of Urban Crisis." *The American Economic Review* :415–426.

Benassy, Jean-Pascal. 1998. "Is there always too little research in endogenous growth with expanding product variety?" *European Economic Review* 42 (1):61–69.

Bergeaud, Antonin, Arthur Guillouzouic, Emeric Henry, and Clément Malgouyres. 2025. "From Public Labs to Private Firms: Magnitude and Channels of Local R&D Spillovers." *The Quarterly Journal of Economics* 140 (4):3233–3282.

Buera, Francisco J and Joseph P Kaboski. 2012. "The Rise of the Service Economy." *American Economic Review* 102 (6):2540–69.

Buera, Francisco J, Joseph P Kaboski, Richard Rogerson, and Juan I Vizcaino. 2022. "Skill-Biased Structural Change." *The Review of Economic Studies* 89 (2):592–625.

Carneiro, Pedro, Kai Liu, and Kjell G Salvanes. 2023. "The Supply of Skill and Endogenous Technical Change: Evidence from a College Expansion Reform." *Journal of the European Economic Association* 21 (1):48–92.

Caselli, Francesco and Wilbur John Coleman II. 2001. "The US Structural Transformation and Regional Convergence: A Reinterpretation." *Journal of Political Economy* 109 (3):584–616.

Ciccone, Antonio and Kiminori Matsuyama. 1996. "Start-Up Costs and Pecuniary Externalities as Barriers to Economic Development." *Journal of Development Economics* 49 (1):33–59.

Comin, Diego, Danial Lashkari, and Martí Mestieri. 2021. "Structural Change with Long-Run Income and Price Effects." *Econometrica* 89 (1):311–374.

Desmet, Klaus and Esteban Rossi-Hansberg. 2009. "Spatial Growth and Industry Age." *Journal of Economic Theory* 144 (6):2477–2502.

———. 2014. "Spatial Development." *American Economic Review* 104 (4):1211–43.

Diamond, Rebecca and Enrico Moretti. 2024. "Where is Standard of Living the Highest? Local Prices and the Geography of Consumption." Working Paper 29533, National Bureau of Economic Research.

Eckert, Fabian and Michael Peters. 2022. "Spatial Structural Change." *NBER Working Paper* No.30489.

Fafchamps, Marcel and Brigit Helms. 1996. "Local Demand, Investment Multipliers, and Industrialization: Theory and Application to the Guatemalan Highlands." *Journal of Development Economics* 49 (1):61–92.

Fisher, Allan GB. 1939. "Production, Primary, Secondary and Tertiary." *Economic Record* 15 (1):24–38.

Gennaioli, Nicola, Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer. 2013. "Human Capital and Regional Development." *The Quarterly Journal of Economics* 128 (1):105–164.

Glaeser, Edward L and David C Maré. 2001. "Cities and Skills." *Journal of Labor Economics* 19 (2):316–342.

Goldin, Claudia and Lawrence F Katz. 2007. "The Race Between Education and Technology: The Evolution of US Educational Wage Differentials, 1890 to 2005." *NBER Working Paper* No.12984.

Goos, Maarten and Alan Manning. 2007. "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." *The Review of Economics and Statistics* 89 (1):118–133.

Gould, Eric D. 2007. "Cities, Workers, and Wages: A Structural Analysis of the Urban Wage Premium." *The Review of Economic Studies* 74 (2):477–506.

Hausman, Naomi. 2022. "University Innovation and Local Economic Growth." *Review of Economics and Statistics* 104 (4):718–735.

Herrendorf, Berthold, Richard Rogerson, and Akos Valentinyi. 2014. "Growth and Structural Transformation." In *Handbook of Economic Growth*, vol. 2. Elsevier, 855–941.

Howard, Greg, Russell Weinstein, and Yuhao Yang. 2024. "Do Universities Improve Local Economic Resilience?" *Review of Economics and Statistics* 106 (4):1129–1145.

Huneeus, Federico and Richard Rogerson. 2024. "Heterogeneous Paths of Industrialization." *Review of Economic Studies* 91 (3):1746–1774.

Kalyani, Aakash, Nicholas Bloom, Marcela Carvalho, Tarek Hassan, Josh Lerner, and Ahmed Tahoun. 2025. "The Diffusion of New Technologies." *The Quarterly Journal of Economics* 140 (2):1299–1365.

Katz, Lawrence F and Kevin M Murphy. 1992. "Changes in Relative Wages, 1963–1987: Supply and Demand Factors." *The Quarterly Journal of Economics* 107 (1):35–78.

Kongsamut, Piyabha, Sergio Rebelo, and Danyang Xie. 2001. "Beyond Balanced Growth." *The Review of Economic Studies* 68 (4):869–882.

Kuznets, S.S. 1966. *Modern Economic Growth: Rate, Structure, and Spread*. Studies in Comparative Economics. Yale University Press.

Laitner, John. 2000. "Structural Change and Economic Growth." *The Review of Economic Studies* 67 (3):545–561.

Lin, Jeffrey. 2011. "Technological Adaptation, Cities, and New Work." *Review of Economics and Statistics* 93 (2):554–574.

Matsuyama, Kiminori. 1992. "Agricultural Productivity, Comparative Advantage, and Economic Growth." *Journal of Economic Theory* 58 (2):317–334.

———. 2009. "Structural Change in an Interdependent World: A Global View of Manufacturing Decline." *Journal of the European Economic Association* 7 (2-3):478–486.

Moretti, Enrico. 2021. "The Effect of High-Tech Clusters on the Productivity of Top Inventors." *American Economic Review* 111 (10):3328–3375.

Ngai, L Rachel and Christopher A Pissarides. 2007. "Structural Change in a Multisector Model of Growth." *American Economic Review* 97 (1):429–443.

Nimier-David, Elio. 2022. "Local Human Capital and Firm Creation: Evidence from the Massification of Higher Education in France." Tech. rep., Working Paper.[1537].

Romer, Paul M. 1987. "Growth Based on Increasing Returns Due to Specialization." *The American Economic Review* 77 (2):56–62.

Russell, Lauren C, Lei Yu, and Michael J. Andrews. 2024. "Higher Education and Local Educational Attainment: Evidence from the Establishment of U.S. Colleges." *Review of Economics and Statistics* 106 (4):1146–1156.

Saiz, Albert. 2010. "The Geographic Determinants of Housing Supply." *The Quarterly Journal of Economics* 125 (3):1253–1296.

Takeda, Kohei. 2023. "The Geography of Structural Transformation: Effects on Inequality and Mobility." Tech. rep., CEP Discussion Paper.

Valero, Anna and John Van Reenen. 2019. "The Economic Impact of Universities: Evidence from Across the Globe." *Economics of Education Review* 68:53–67.

Van Agtmael, Antoine and Fred Bakker. 2016. *The Smartest Places on Earth: Why Rustbelts Are the Emerging Hotspots of Global Innovation.* Hachette UK.

Online Appendix to "Universities and the Rise of Services"

Chang Liu Kohei Takeda

A Theory Appendix **A1**

B Appendix for the Quantitative Model **A13**

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Outline of the Appendix

Appendix A provides proofs and derivations for the Propositions and analytical expressions in Section 4 of the main text. Appendix B provides details on the quantitative model. Appendix D describes our datasets in detail and presents descriptive statistics. In Appendix E, we provide results for the robustness tests and additional empirical exercise.

A Theory Appendix

A.1 Production

Production of Tasks A worker (ℓ) supplies one unit of labor to produce $z^{\ell}(j)$ units of task j if they perform task $j \in \mathfrak{R}_+$. Analogously, the labor productivity of creators is given by $z^{c}(j)$. The labor productivity is continuous and satisfies: $z^{\ell\prime}(j) < 0$ and $z^{c\prime}(j) < 0$ so that performing higher-order tasks requires more labor units. In addition, we assume that the relative productivity of workers to creators is decreasing in task index:

$$\frac{d}{dj}\frac{z^{\ell}(j)}{z^{c}(j)} < 0 \tag{A.1}$$

The unit cost of task j is:

$$\gamma(j) = \min\left\{\frac{w^{\ell}}{z^{\ell}(j)},\ \frac{w^{c}}{z^{c}(j)}\right\} \tag{A.2}$$

We let j^* refer the task, at which we have:

$$\frac{w^{\ell}}{z^{\ell}(j^*)} = \frac{w^{c}}{z^{c}(j^*)} \tag{A.3}$$

Therefore we express the unit cost of task by $\gamma(j) = \gamma(j : j^*, w^{\ell}, w^{c})$, which is continuous and increasing in j.

Production of Manufacturing Goods The market for manufacturing goods is competitive, and firms produce homogeneous goods that are freely tradable. We assume that the functional form of production technology of manufacturing firms is Cobb-Douglas, as follows:

$$m = \exp\left[\int_0^1 \beta(j)\ln\left(\frac{x(j)}{\beta(j)}\right)dj\right], \quad 0 < \beta(j) < 1, \quad \int_0^1 \beta(j)dj = 1 \tag{A.4}$$

where $x(j)$ refer input of task j. Firms' profit maximization implies:

$$\gamma(j)\,x(j) = \beta(j)qm, \tag{A.5}$$

and zero profits lead to:

$$q = \exp\left[\int_0^1 \beta(j)\ln\gamma(j)dj\right]. \tag{A.6}$$

In the following we also use the notation:

$$\overline{\beta}(j) = \int_0^j \beta(s)ds \leq 1$$

which is the expenditure share of manufacturing firms on tasks up to the task indexed by j.

Production of Services The market for tasks is competitive, and all tasks produced by non-college or college graduates are used in the production of manufacturing goods and services. We assume that the functional form of production technology of services is constant elasticity of substitution (CES) with elasticity ε as follows:

$$y = J^{\tilde{\nu}+\frac{1}{1-\varepsilon}-1}\left[\int_0^J x(j)^{\frac{\varepsilon-1}{\varepsilon}}dj\right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{A.7}$$

When the elasticity of substitution $\varepsilon < 1$, complementarity across tasks in production weighs more on tasks that services firms are least successful. In the following, we let

$$\nu = \tilde{\nu} + \frac{1}{1-\varepsilon} - 1 \tag{A.8}$$

Service producers follow perfect competition, as there is a large number of firms. Profit maximization problem is:

$$\max_{\{x(j)\}} \; p\, J^{\nu} \left[\int_0^J x(j)^{\frac{\varepsilon-1}{\varepsilon}} dj \right]^{\frac{\varepsilon}{\varepsilon-1}} - \int_0^J \gamma(j) x(j)\, dj$$

First order condition implies:

$$x(j) = J^{(\varepsilon-1)\nu} \frac{\gamma(j)^{-\varepsilon} y}{p^{-\varepsilon}}$$

and plugging this into the production function leads to the production cost of one unit of service using tasks, which is equal to its price:

$$p(j^*, J, w_\ell, w_c) = \frac{1}{J^{\nu}} \left[\int_0^{j^*} \left(\frac{w_\ell}{z_\ell(j)} \right)^{1-\varepsilon} dj + \int_{j^*}^J \left(\frac{w_c}{z_c(j)} \right)^{1-\varepsilon} dj \right]^{\frac{1}{1-\varepsilon}}, \tag{A.9}$$

where, in the bracket of the right-hand side, the first term is the input costs of tasks performed by non-college graduates and the second term is those performed by college graduates. In the followings, we use $p = p(j^*, J, w_\ell, w_c)$ to simplify the notation.

A.2 Market Clearing

Goods and Services Market Both types of workers have the same preference over goods and services. Since the goods are freely traded with the outer world, we normalize the price: $q = 1$. Then, the market clearing condition for goods and services are:

$$m = (1-\alpha)X, \quad py = \alpha X, \tag{A.10}$$

where X is the total expenditure of workers. Zero profit condition implies that the payment to tasks of service firms is given by αX.

Task and Labor Market The expenditure share of service firms on different tasks j of inputs is:

$$\theta(j) = \frac{\gamma(j)x(j)}{\int_0^J \gamma(j')x(j')\, dj'} = \frac{\gamma(j)^{1-\varepsilon}}{\int_0^J \gamma(j')^{1-\varepsilon} dj'} \tag{A.11}$$

This is continuous function $[0, J] \to (0, 1)$. Note two properties for the expenditure pattern of service firms. First, it is straightforward to see that the expenditure share on incumbent task decreases as a firm uses a wider range of tasks. Second, $\theta(j_0) > \theta(j_1)$ if $j_0 < j_1$, implying the expenditure share on tasks is increasing in task index.

The labor market clearing condition for non-college graduates is:

$$w_\ell L_\ell = \underbrace{(1-\alpha)\overline{\beta}(j^*)X}_{\text{Manufacture labor demand}} + \underbrace{\alpha X \int_0^{j^*} \theta(\tau) d\tau}_{\text{Service labor demand}}, \tag{A.12}$$

Analogously, the labor market clearing condition for college graduates is:

$$w_c L_c = (1-\alpha)X[1-\overline{\beta}(j^*)] + \alpha X \int_{j^*}^{J} \theta(\tau)\, d\tau \tag{A.13}$$

where, on the right-hand side, the first term is the payment to college graduates in the manufacturing sector, and the second term is the payment to them in the services sector.

When we take the ratio of equations (A.12) and (A.13), we obtain:

$$\frac{w_\ell}{w_c}\frac{L_\ell}{L_c} = \frac{(1-\alpha)\overline{\beta}(j^*)X + \alpha X \int_0^{j^*} \theta(\tau) d\tau}{(1-\alpha)X[1-\overline{\beta}(j^*)] + \alpha X \int_{j^*}^{J} \theta(\tau)\, d\tau} \tag{A.14}$$

Rearranging this yields the wage curve $\Gamma(j^*, \frac{L_c}{L_\ell}, J)$ displayed in equation (7) of the main text. The wage curve summarizes the relative demand for different types of workers given the equilibrium task assignment j^*, frontier of tasks J and relative endowment of workers L_c/L_ℓ.

A.3 Proof of Propositions in Section 4

Proof of Proposition 1 We substitute (A.11) into the second term of the right-hand side of equations (A.12) and (A.13) and use (**??**) to obtain:

$$\alpha Y \int_1^J x(\tau, J) \left[\int_0^{j^*} \vartheta(j,\tau) dj\right] d\tau = \alpha Y w^\ell \int_1^J p(\tau)^{-\eta} Q(\tau, J) \left[\int_0^{j^*} \frac{1}{z^\ell(j)} dj\right] d\tau \tag{A.15}$$

and

$$\alpha Y \int_1^K x(\tau, J) \left[\int_{j^*}^{K} \vartheta(j,\tau) dj\right] d\tau = \alpha Y w^c \int_1^J p(\tau)^{-\eta} Q(\tau, J) \left[\int_{j^*}^{J} \frac{1}{z^c(j)} dj\right] d\tau \tag{A.16}$$

Using them, we define two functions as follows:

$$\Gamma^\ell(j, w^\ell, J) \equiv (1-\alpha)\overline{\beta}(j) + \alpha w^\ell \int_1^J p(\tau)^{-\eta} Q(\tau, J) \left[\int_0^{j^*} \frac{1}{z^\ell(j)} dj\right] d\tau \tag{A.17}$$

and

$$\Gamma^c(j, w^c, J) \equiv (1-\alpha)[1-\overline{\beta}(j)] + \alpha w^c \int_1^J p(\tau)^{-\eta} Q(\tau, J) \left[\int_{j^*}^{J} \frac{1}{z^c(j)} dj\right] d\tau \tag{A.18}$$

These two functions $\Gamma^\ell(j, w^\ell, J)$ and $\Gamma^c(j, w^c, J)$ are continuous in $j \in \mathfrak{R}_+$. In addition, these two functions show that: (i) $\Gamma^\ell(j, w^\ell, J)$ is increasing and $\Gamma^c(j, K, w^c)$ is decreasing in j given wages (w^ℓ, w^c) and frontier (K), (ii) when $j = 0$, we have $\Gamma^\ell(0, K, w^\ell) = 0$ and $\Gamma^c(0, K, w^c) > 0$, and (iii) when $j \to K$, we have $\lim_{j\to K} \Gamma^\ell(j, K, w^\ell) > 0$ and $\lim_{j\to K} \Gamma^c(j, K, w^c) = 0$. Using these functions, the wage curve (7) can be written as:

$$\Gamma\left(j, \frac{L^c}{L^\ell}, K\right) = \frac{\Gamma^\ell(j, K, w^\ell)}{\Gamma^c(j, K, w^c)} \frac{L^c}{L^\ell} \tag{A.19}$$

Without loss of generality, we set the workers' wage to one: $w^\ell = 1$. The equilibrium is defined by j^* and w^c that solve the equations:

$$\frac{z^\ell(j^*)}{z^c(j^*)} = \frac{\Gamma^\ell(j^*, K, 1)}{\Gamma^c(j^*, K, w^c)} \frac{N^c}{N^\ell} \tag{A.20}$$

and

$$\frac{1}{w^c} = \frac{z^\ell(j^*)}{z^c(j^*)} \tag{A.21}$$

given frontier K and number of workers (L^ℓ) and creators (L^c).

The right-hand side of equation (A.20) shows that the following properties:

$$\frac{d}{dj}\frac{\Gamma^\ell(j, K, 1)}{\Gamma^c(j, K, w^c)}\bigg|_{K, w^c} > 0, \quad \frac{\partial}{\partial w^c}\frac{\Gamma^\ell(j, K, 1)}{\Gamma^c(j, K, w^c)}\bigg|_{K} < 0,$$
$$\frac{\Gamma^\ell(0, K, 1)}{\Gamma^c(0, K, w^c)} = 0, \quad \lim_{j \to K} \frac{\Gamma^\ell(j, K, 1)}{\Gamma^c(j, K, w^c)} = \infty$$

The intuitions for the first two relationships are as follows. First, if the assignment of tasks j increases, more tasks are performed by workers and fewer tasks are performed by creators. This leads to higher expenditure on workers and lower expenditure on creators, resulting in an increase in the relative expenditure on the right-hand side of (A.20). Second, when the wage of creators (w^c) increases, expenditure on tasks performed by creators increases while that of workers decreases, given the task assignment.

Therefore, the relative expenditure on the right-hand side of (A.20) decreases, and there exists a unique task assignment j^* given wage w^c that solves (A.20). Then, the equilibrium wage (w^c) is adjusted to solve (A.20) and (A.21) together. Once we have the task assignment (j^*) and wage (w^c), other endogenous variables are determined. The manufacturing goods price is determined by equation (A.6), and the service prices are determined by equation (A.9). ■

Proof of Proposition 2 (i) It is straightforward to see the impact of relative change in the mass of creators to workers, L^c/L^ℓ. Since the wage curve $\Gamma(j, L^c/L^\ell, K)$ increases in L^c/L^ℓ for all tasks $j \in \mathfrak{N}_+$ and given K as in equation (A.19), the upward shift of the wage curve leads to an increase in relative wage ω (i.e., lower w^c). This further shifts the wage curve upward, and the task set for workers $[0, j^*]$ expands.

Proof of Proposition 2 (ii) Suppose that the frontier changes from K_0 to $K_1 > K_0$, and the wage curve shows the shift as in (8). Namely, we consider the shift of the wage curve such that:

$$\frac{\Gamma^\ell(j, K_0, w^\ell)}{\Gamma^c(j, K_0, w^c)} > \frac{\Gamma^\ell(j, K_1, w^\ell)}{\Gamma^c(j, K_1, w^c)} \tag{A.22}$$

for any $j \in [0, K_0]$ given the mass of workers and creators. This is the case in which the wage curve becomes flatter when the frontier shits toward right, as in the right-hand panel of Figure 6 in the main text. To show this, we consider the derivative of $\Gamma^\ell(\sigma, K, 1)$:

$$\frac{\partial}{\partial j}\Gamma^\ell(j, K, w^\ell) = (1-\alpha)\beta(j) + \frac{\alpha w^\ell}{z^\ell(j)}\int_1^K \frac{x(\tau, K)}{p(\tau)}d\tau$$

Suppose that the frontier task K_0 shifts to K_1. For the incumbent services $[1, K_0]$, expenditure share decreases given the price. In addition, the price of services can be low due to task reallocation from creators to workers in inputs, and it can be high if the creators' wages increase sufficiently.

We assume that (a) the price of new services become sufficiently high; and (b) the expenditure share for new services is sufficiently small, so that we have:

$$\int_1^{K_0} \frac{x(\tau, K_0)}{p(\tau)}d\tau > \int_1^{K_1} \frac{x(\tau, K_1)}{p(\tau)}d\tau \tag{A.23}$$

It follows that:

$$\frac{\partial}{\partial j}\Gamma^\ell(j, J, w^\ell)\Big|_{J=J_0} > \frac{\partial}{\partial j}\Gamma^\ell(j, J, w^\ell)\Big|_{J=J_1}, \tag{A.24}$$

and for the creators, we obtain:

$$\frac{\partial}{\partial j}\Gamma^c(j, K, w^c)\Big|_{J=J_0} < \frac{\partial}{\partial j}\Gamma^c(j, K, w^c)\Big|_{J=J_1} \tag{A.25}$$

Together, the wage curve becomes flat and shifts down for all incumbent $j \in (0, J_0]$. Given the relative productivity curve $z^\ell(j)/z^c(j)$, we see that the wage ratio ω_0 decreases (i.e., w^c increases) to ω_1 and the threshold of tasks j_0^* increases to the new level j_1^* in equilibrium. In addition, an increase in w^c leads to a further shift down of the wage curve, implying lower ω_1 and higher j_1^*. ■

Proof of Proposition 2 (iii) Suppose that $z_0^\ell(j)/z_0^c(j)$ changes to $z_1^\ell(j)/z_1^c(j)$ as follows: (a) workers can do wider range of tasks such that they could perform tasks $[0, \bar{j}_0]$ with $z_0^\ell(\bar{j}_0)/z_0^c(\bar{j}_0) = 0$ before and they can be able to perform tasks $[0, \bar{j}_1]$ with $z_1^\ell(\bar{j}_1)/z_1^c(\bar{j}_1) = 0$ with $\bar{j}_1 > \bar{j}_0$; and (b) the relative productivity shows $z_1^\ell(j)/z_1^c(j) > z_0^\ell(j)/z_0^c(j)$ for any $j < \bar{j}_1$. This is captured by the rightward shift of the relative productivity curve in Figure 5 of the main text. As a result, we have an increase in the wage ratio ω^* and task threshold (j^*). ■

Proof of Proposition 3 In the model, the mass of labor inputs in the service sector equals the mass of workers and creators producing tasks used by the service firms. In this point of view, rewriting equations (A.12) and (A.13), the mass of labor inputs in the service is given by:

$$E_{\text{Service}} = \alpha\left[\int_1^J \frac{x(\tau, J)}{w^\ell}\left(\int_0^{j^*}\vartheta(j,\tau)dj\right)d\tau + \int_1^J \frac{x(\tau, J)}{w^c}\left(\int_{j^*}^{J}\vartheta(j,\tau)dj\right)d\tau\right]Y, \tag{A.26}$$

where we combine the labor inputs for tasks below j^* (the first term) performed by workers and tasks between j^* and J (the second term) performed by creators. Plugging equations (A.15) into the right-hand side of equation (A.26), we obtain:

$$E_{\text{Service}} = \alpha Y \left(\int_1^J p(\tau)^{-\eta} Q(\tau, J) d\tau \right) \left[\int_0^{j^*} \frac{1}{z^\ell(j)} dj + \int_{j^*}^J \frac{1}{z^c(j)} dj \right] \tag{A.27}$$

Using equation (A.9), the price of service based on the task in frontier J is:

$$p(J) = \int_0^{j^*} \frac{w^\ell}{z^\ell(j)} dj + \int_{j^*}^J \frac{w^c}{z^c(j)} dj \tag{A.28}$$

and so

$$\int_{j^*}^J \frac{1}{z^c(j)} dj = \frac{p(J)}{w^c} - \omega \int_0^{j^*} \frac{1}{z^\ell(j)} dj \tag{A.29}$$

When we substitute this into (A.27), the employment in the service sector in equilibrium is:

$$E_{\text{Service}} = D_{\text{Service}} \left[(1-\omega) \int_0^{j^*} \frac{1}{z^\ell(j)} dj + \omega p(J) \right] \tag{A.30}$$

where we define the aggregate consumption of services:

$$D_{\text{Service}} = \alpha Y \left(\int_1^J p(\tau)^{-\eta} Q(\tau, J) d\tau \right), \tag{A.31}$$

To begin with, we let wages (w^n, w^c, and so ω) and J be fixed and focus on the change in j^*. If j^* increases, workers perform a larger set of tasks, while creators perform higher-order tasks that are used intensively as inputs in the service sector. The first term in the bracket of the equation (A.30) increases. In the second term, the service price $p(J)$ decreases as the input share of workers increases in the frontier service as well. If the relative wage ratio ($\omega = w^\ell / w^c$) is small (i.e., skill premium is high), the first effect and an increase in demand dominate the lower price of frontier service. Therefore, the task reallocation leads to an increase in the labor force in the service sector.

New tasks and labor share in Proposition 4 and 5 Suppose that the frontier changes from J_0 to J_1, and we use subscript 0 for the equilibrium under J_0 and subscript 1 for that under J_1. First, we consider two terms in the bracket of equation (A.30). As we discussed in Proposition 2, the equilibrium wage ratio decreases when the frontier shifts to expand the set of tasks:

$$\omega_0^* > \omega_1^*$$

The threshold of the task assignment is also shifted to the right: $j_0^* < j_1^*$, which leads to:

$$\int_0^{j_0^*} \frac{1}{z^\ell(s)} ds < \int_0^{j_1^*} \frac{1}{z^\ell(s)} ds$$

This captures how the demand for workers performing tasks for services increases because of the reallocation of tasks. Lastly, if

$$\omega_1^* p_1(J_1) > \omega_0^* p_0(J_0) \;\Leftrightarrow\; \frac{p(J_1)}{p(J_0)} > \frac{1/\omega_1^*}{1/\omega_0^*},$$

we have E_{Service} increases. This states the relationship between the change in the production cost of services and that of the creator's wage. In particular, the price of the frontier services increases more than the increase in the wage premium. The effects are more pronounced if the demand for new services is large such that overall demand for services (D_{Service}) increases.

Turning to the manufacturing sector, (A.12) and (A.13) imply that the mass of labor in the manufacturing sector is:

$$E_{\text{Man.}} = (1-\alpha)\left\{\overline{\beta}(j^*)\left(L^\ell + \frac{1}{\omega^*}L^c\right) + \left[1-\overline{\beta}(j^*)\right]\left(\omega^* L^\ell + L^c\right)\right\} \tag{A.32}$$

Given the expansion of the task frontier, the mass of workers in the manufacturing sector increases when $\overline{\beta}(j^*)$ increases and wage premium $1/\omega^*$ increases, while the mass of creators in the manufacturing sector decreases.

A.4 Analytical Results using Functional Forms

To shed light on the mechanisms underlying our results, we impose particular functional forms for the productivity functions $z^\ell(j)$ and $z^c(j)$ and derive the results analytically. In particular, we posit the following specification:

$$z^\ell(j) = \Omega^\ell e^{-j}, \quad z^c(j) = \Omega^c e^{-\varepsilon j}, \quad \varepsilon < 1 \tag{A.33}$$

These functions imply that the relative productivity is:

$$\mathcal{Z}(j) \equiv \frac{z^\ell(j)}{z^c(j)} = \left(\frac{\Omega^\ell}{\Omega^c}\right) e^{-(1-\varepsilon)j}$$

and this is a decreasing and convex function. Equation (A.3) implies that task assignment rule j^* satisfies:

$$j^* = \frac{1}{1-\varepsilon}\ln\left(\frac{w^c/\Omega^c}{w^\ell/\Omega^\ell}\right) \tag{A.34}$$

The labor market clearing condition becomes:

$$\frac{w^\ell}{w^c} = \frac{(1-\alpha)\overline{\beta}(j) + \alpha\frac{w^\ell}{\Omega^\ell}(e^{j^*}-1)y^S}{(1-\alpha)[1-\overline{\beta}(j)] + \alpha\frac{w^c}{\varepsilon\Omega^c}\left(e^{\varepsilon K} - e^{\varepsilon j^*}\right)y^S}\frac{L^c}{L^\ell} \tag{A.35}$$

where we use the notation:

$$y^S = \int_1^K p(\tau)^{-\eta} Q(\tau, K)\, d\tau$$

for the aggregate consumption units of services.

The equilibrium is determined by equations (A.34) and (A.35). When we combine them, the threshold for the task allocation solves the following equation:

$$\frac{1-\alpha}{\alpha}\left[\left(\frac{\Omega^{\ell}}{\Omega^{c}}\right)e^{-(1-\varepsilon)j^{*}}\left(1-\overline{\beta}(j^{*})\right)N^{\ell}-\overline{\beta}(j^{*})N^{c}\right]=\left[\frac{w^{\ell}}{\Omega^{\ell}}\left(e^{j^{*}}-1\right)N^{c}-\frac{1}{\varepsilon}\left(\frac{w^{\ell}}{\Omega^{c}}\right)\left(e^{\varepsilon K}-e^{\varepsilon j^{*}}\right)N^{\ell}\right]y^{S} \tag{A.36}$$

Given the aggregate demand schedule of services (y^{S}), we have the following results: first, the left-hand side of (A.36) is decreasing and the right-hand side of (A.36) is increasing in j^{*}; second, equation (A.34) implies that relative wage of creators increases when the tasks are reallocated from creators to workers $\frac{d\log w^{c}/w^{\ell}}{d\sigma^{*}}>0$; third, an increase in K shifts down the right-hand side of (A.36) therefore the equilibrium task allocation j^{*} moves toward right; and fourth, when the expenditure share of the manufacturing sector shifts toward the right (i.e., the distribution of $\beta(j)$ shifts toward the right), the left-hand side of (A.36) shifts upward and the task threshold j^{*} increases.

Next, the sectoral employment (A.27) in the service sector is:

$$L_{\text{Service}}=(\Omega^{\ell}+\Omega^{c})\left[\frac{\Omega^{\ell}}{\Omega^{\ell}+\Omega^{c}}\left(e^{j^{*}}-1\right)+\frac{\Omega^{c}}{\Omega^{\ell}+\Omega^{c}}\frac{1}{\varepsilon}\left(e^{\varepsilon K}-e^{\varepsilon j^{*}}\right)\right]\overline{Q}(K) \tag{A.37}$$

Then, we obtain:

$$\left.\frac{\partial L_{\text{Service}}}{\partial j^{*}}\right|_{\overline{Q}(K)}\propto\Omega^{\ell}e^{j^{*}}-\Omega^{c}e^{\varepsilon j^{*}}=e^{\varepsilon j^{*}}\left[\frac{\Omega^{\ell}}{e^{-(1-\varepsilon)j^{*}}}-\Omega^{c}\right]$$

Using equation (A.3), we obtain:

$$\frac{w^{c}}{w^{\ell}}\geq\left(\frac{\Omega^{c}}{\Omega^{\ell}}\right)^{2}\implies\left.\frac{\partial L_{\text{Service}}}{\partial j^{*}}\right|_{\overline{Q}(K)}\geq 0 \tag{A.38}$$

We also confirm:

$$\left.\frac{\partial L_{\text{Service}}}{\partial K}\right|_{\overline{Q}(K)}\propto e^{\varepsilon K}>0 \tag{A.39}$$

Lastly, we consider the demand shift. Under the parametrization, the cost of each task is:

$$\gamma(j)=\frac{w^{\ell}}{\Omega^{\ell}}e^{j},\quad j\in[0,j^{*}]$$
$$\gamma(j)=\frac{w^{c}}{\Omega^{c}}e^{\varepsilon j},\quad j\in[j^{*},K]$$

The price of service is:

$$p(\tau)=\frac{w^{\ell}}{\Omega^{\ell}}(e^{j^{*}}-1)+\frac{w^{c}}{\Omega^{c}}\frac{1}{\varepsilon}(e^{\varepsilon\tau}-e^{\varepsilon j^{*}}) \tag{A.40}$$

When we compare the two equilibrium when the task frontier shifts from K_0 to K_1, we have

$$p_1(\tau) - p_0(\tau) = \frac{1}{\Omega^\ell}\left[w_1^\ell(e^{j_1^*}-1) - w_0^\ell(e^{j_0^*}-1)\right] + \frac{1}{\varepsilon\Omega^c}\left[(w_1^c - w_0^c)e^{\varepsilon\tau} - w_1^c e^{\varepsilon j_1^*} + w_0^c e^{\varepsilon j_0^*}\right]$$

Using the equilibrium condition, we obtain:

$$\begin{aligned} p_1(\tau) \geq p_0(\tau) \;&\Leftrightarrow\; e^{\varepsilon\tau} \geq \frac{\Omega^c}{\Omega^\ell}\left[\varepsilon\frac{w_1^\ell - w_0^\ell}{w_1^c - w_0^c} + (1-\varepsilon)\frac{w_1^\ell e^{j_1^*} - w_0^\ell e^{j_0^*}}{w_1^c - w_0^c}\right] \\ &\Leftrightarrow\; e^{\varepsilon\tau} \geq \frac{\Omega^c}{\Omega^\ell}\frac{w_o^\ell}{w_0^c}\left[\varepsilon\frac{\widehat{w}^\ell - 1}{\widehat{w}^c - 1} + (1-\varepsilon)\frac{\widehat{w}^\ell e^{j_1^*} - e^{j_0^*}}{\widehat{w}^c - 1}\right] \end{aligned} \tag{A.41}$$

where $\widehat{w}^\theta = w_1^\theta / w_0^\theta$ is wage changes. For larger indices of services (i.e., large τ), their prices increase, and the demand for them decreases. In addition, when wage growth of creators is higher than workers ($\widehat{w}^c > \widehat{w}^\ell$), more services increase prices. When the task allocation shows a rightward shift, more services decrease prices. Overall effect is ambiguous. If a decrease in demand for the high-indexed services is small enough to be compensated by an increase in demand for the low-indexed services, aggregate demand and the service employment (A.37) increases.

A.5 Skill-biased technical change

In equilibrium we have:

$$\frac{w^c}{w^\ell} = \frac{(1-\alpha)\left[1-\overline{\beta}(j^*)\right] + \alpha\displaystyle\int_1^K x(s,K)\left[\int_{j^*}^K \vartheta(j,s)dj\right]ds}{(1-\alpha)\overline{\beta}(j^*) + \alpha\displaystyle\int_1^K x(s,K)\left[\int_0^{j^*} \vartheta(j,s)dj\right]ds}\frac{N^\ell}{N^c} \tag{A.42}$$

This implies:

$$d\ln\left(\frac{w^c}{w^\ell}\right) = -d\ln\left(\frac{N^c}{N^\ell}\right) + d\ln\underbrace{\frac{\Phi^c(j^*,K)}{\Phi^\ell(j^*,K)}}_{\Phi(j^*,K)} \tag{A.43}$$

where we define:

$$\begin{aligned} \Phi^c(j^*,K) &\equiv (1-\alpha)\left[1-\overline{\beta}(j^*)\right] + \alpha\int_1^K x(s,K)\left[\int_{j^*}^K \vartheta(j,s)dj\right]ds, \\ \Phi^\ell(j^*,K) &\equiv (1-\alpha)\overline{\beta}(j^*) + \alpha\int_1^K x(s,K)\left[\int_0^{j^*} \vartheta(j,s)dj\right]ds \end{aligned} \tag{A.44}$$

We have:

$$d\ln\left[\frac{\Phi^c(j^*,K)}{\Phi^\ell(j^*,K)}\right] = \underbrace{\left(\frac{\partial\ln\Phi}{\partial j^*}\right)dj^*}_{\text{Task allocation}} + \underbrace{\left(\frac{\partial\ln\Phi}{\partial K}\right)dK}_{\text{Frontier task}} \tag{A.45}$$

First, holding K fixed, the effect of changing task allocation j^* is:

$$\begin{aligned}\frac{\partial \Phi^c}{\partial j^*} &= -(1-\alpha)\beta(j^*) - \alpha \int_1^K x(s,K)\vartheta(j^*,s)ds, \\ \frac{\partial \Phi^\ell}{\partial j^*} &= (1-\alpha)\beta(j^*) + \alpha \int_1^K x(s,K)\vartheta(j^*,s)ds\end{aligned} \tag{A.46}$$

and

$$\frac{\partial \ln \Phi}{\partial j^*} = -\left[(1-\alpha)\beta(j^*) + \alpha \int_1^K x(s,K)\vartheta(j^*,s)ds\right]\left(\frac{1}{\Phi^\ell} + \frac{1}{\Phi^c}\right)$$

Second, the effect of changing K with j^* held fixed is:

$$\begin{aligned}\frac{\partial \Phi^c}{\partial K} &= \alpha\left[x(K,K)\int_{j^*}^K \vartheta(j,K)dj + \int_1^K \frac{\partial x(s,K)}{\partial K}\left(\int_{j^*}^K \vartheta(j,s)dj\right)ds + \int_1^K x(s,K)\vartheta(K,s)ds\right], \\ \frac{\partial \Phi^\ell}{\partial K} &= \alpha\left[x(K,K)\int_0^{j^*} \vartheta(j,K)dj + \int_1^K \frac{\partial x(s,K)}{\partial K}\left(\int_0^{j^*} \vartheta(j,s)dj\right)ds\right]\end{aligned} \tag{A.47}$$

Suppose that (i) expenditure share on the frontier service is sufficiently small $x(K,K) \approx 0$; and (ii) change in expenditure share on service s is small $\frac{\partial x(s,K)}{\partial s} \approx 0$. Then, we obtain the simple representation as follows:

$$\frac{\partial \ln \Phi}{\partial K} = \alpha \frac{\int_1^K x(s,K)\vartheta(K,s)ds}{\Phi^c} \tag{A.48}$$

Combining them together, we obtain:

$$\begin{aligned}d\ln\left[\frac{\Phi^c(j^*,K)}{\Phi^\ell(j^*,K)}\right] = &-\left[(1-\alpha)\beta(j^*) + \alpha\gamma(j^*)\int_1^K \frac{x(s,K)}{p(s)}ds\right]\left(\frac{1}{\Phi^\ell} + \frac{1}{\Phi^c}\right)dj^* \\ &+ \alpha\gamma(K)\int_1^K \frac{x(s,K)}{p(s)}ds\frac{1}{\Phi^c}dK,\end{aligned} \tag{A.49}$$

When we use the cost share of a task in the production of differentiated service, we have:

$$\int_1^K \frac{\alpha x(s,K)}{p(s)}ds = \left[\int_1^K q(s,K)ds\right]\frac{1}{Y} \tag{A.50}$$

where $q(s,K)$ is consumption of service s. Using this, we define the average price index for services:

$$P = \frac{Y}{\int_1^K q(s,K)ds} \tag{A.51}$$

Using the price index, we have:

$$d\ln\left[\frac{\Phi^c(j^*,K)}{\Phi^\ell(j^*,K)}\right] = -\left[(1-\alpha)\beta(j^*) + \frac{\gamma(j^*)}{P}\right]\left(\frac{1}{\Phi^\ell} + \frac{1}{\Phi^c}\right)dj^* + \frac{\gamma(K)}{P}\frac{1}{\Phi^c}dK, \tag{A.52}$$

The first term captures the effect of task allocation in which the skill premium rises when the task boundary (j^*) moves $dj^* < 0$. In theory, j^* decreases when N^c/N^ℓ increases. Let us define the elasticity of the task boundary with respect to relative supply:

$$dj^* = -\underbrace{\frac{\partial j^*}{\partial \ln(N^c/N^\ell)}}_{=\mathcal{E}} d\ln\left(\frac{N^c}{N^\ell}\right), \quad \mathcal{E} > 0 \tag{A.53}$$

Then we obtain the following decomposition that is reminiscent of the skill-biased technical change:

$$d\ln\left(\frac{w^c}{w^\ell}\right) = -\left[1 - \mathcal{E}\left((1-\alpha)\beta(j^*) + \frac{\gamma(j^*)}{P}\right)\left(\frac{1}{\Phi^\ell} + \frac{1}{\Phi^c}\right)\right] d\ln\left(\frac{N^c}{N^\ell}\right) + \frac{\gamma(K)}{P}\frac{1}{\Phi^c}dK \tag{A.54}$$

On the right-hand side, the first bracket term is the effective elasticity of skill premium to supply. If $\mathcal{E}$ is large, the coefficient becomes small and the direct effect of labor supply is offset by task reallocation. The second term is the effect of the expansion of tasks. When new tasks become technologically feasible, $dK > 0$. These new tasks are skill-intensive since they enter at the top end of the task set, so they disproportionately raise wage premium and its magnitude becomes large when the cost of frontier task $\gamma(K)$ is high and service price (P) is low. This term is pure technology-driven skill bias, analogous to the skill-biased technical change term out of a standard CES-based skill-biased technology, as we discuss next.

Connection to CES Skill-Biased Technical Change (Katz and Murphy 1992) Here is the equilibrium equation for the skill-biased technical change:

$$d\ln\frac{w^c}{w^\ell} = -\frac{1}{\sigma}d\ln\frac{N^c}{N^\ell} + \frac{\sigma-1}{\sigma}d\ln\frac{A^c}{A^\ell} \tag{A.55}$$

where w^c/w^ℓ is the skill premium, N^c/N^ℓ is the relative supply of skills, σ is the elasticity of substitution between skilled and unskilled workers, and A^ℓ and A^c are factor-augmenting technologies for unskilled and skilled workers, respectively. This comes from CES aggregator for skilled and low-skilled labor, and A^c/A^ℓ is exogenous. Our model provides a micro foundation for this technology term. In particular, we show that relative productivity is determined by the allocation of tasks (j^*) and the expansion of the technology frontier (K). In particular, an increase in the relative labor supply leads to task reallocation, attenuating the supply elasticity; and the expansion of frontier tasks introduces new skill-intensive tasks. Thus, our model captures the interaction between supply and technology that the CES framework abstracts from.

Connection to Task-Based Skill-Biased Technical Change (Acemoglu and Restrepo 2020) Acemoglu and Restrepo (2020) extend the canonical skill-biased structural change equation by adding

a term for task reallocation:

$$d\ln\frac{w^c}{w^\ell} = -\frac{1}{\sigma}d\ln\frac{N^c}{N^\ell} + \frac{\sigma-1}{\sigma}d\ln\frac{A^c}{A^\ell} + \frac{1}{\lambda}d\ln\frac{\Gamma^c}{\Gamma^\ell} \tag{A.56}$$

where the third term on the right-hand side captures the task allocation effect, that is, change in the share of tasks performed by skilled vs unskilled labor. This term allows technology to affect wage premiums by changing the task content of production, not just by augmenting productivity in all tasks. Our theoretical framework aligns with the model since we (i) emphasize task allocation and new tasks as drivers of skill bias; and (ii) show that technology and supply interact through task boundaries.

However, our model differ from theirs of an aggregate index (Γ^c/Γ^ℓ) in three aspects. First, we model the task boundary (j^*) and technology frontier (K) explicitly. Second, we introduce an elasticity $\mathcal{E}$ that quantifies how relative supply shifts affect task allocation. Third and foremost, our model allows us to isolate the frontier technology progress as a distinct source of technology-driven skill bias. This decomposition in Equation (A.54) clarifies how supply and technology interact, making the drivers of skill premium changes more quantitatively interpretable.

B Appendix for the Quantitative Model

B.1 General Equilibrium

The equilibrium distribution of economic activities across locations is determined by (i) the set of parameters in $(\alpha, \mu_i, \varphi^k, \beta, \sigma, \varepsilon)$; (ii) the task performance of college graduates $z_c(j)$ and non-college graduates $z_\ell(j)$; and (iii) the heterogeneity across locations in the mass of non-college graduates $\{L_{\ell n}\}$, task-neutral productivity $\{A_n^k\}$, productivity of developers $\{G_n\}$, amenities $\{B_n\}$, and total number of creators in the country $(\bar{L}_c)$.

Given the exogenous primitives of the model and economy-wide parameters, the equilibrium is characterized by wages $\{w_{in}\}$, the distribution of college graduates $\{L_{cn}\}$, the task assignment $\{j_n^*\}$, the frontier of tasks $\{J_n\}$, floor space prices $\{r_n\}$ and common real income $(\bar{v}^c)$ that solve the following system of equations:

$$\gamma_n(j) = \min\left\{\frac{w_{\ell n}}{a_{\ell n}z_\ell(j)}, \frac{w_{cn}}{a_{cn}z_c(j)}\right\}, \tag{B.1}$$

$$\frac{w_{\ell n}}{w_{cn}} = \frac{a_{\ell n}z_\ell(j_n^*)}{a_{cn}z_c(j_n^*)}, \tag{B.2}$$

$$\frac{w_{cn}B_n}{\left(\mathbb{P}_n\right)^{\mu_c}\left(r_n\right)^{1-\mu_c}} = \bar{v}^c, \tag{B.3}$$

$$Y_n^M = \pi_n \sum_{i\in\{\ell,c\}}\sum_{n'\in\mathcal{R}} \xi_{n'}^M \mu_i w_{in'}L_{in'}, \tag{B.4}$$

$$Y_n^S = \sum_{i\in\{\ell,c\}} \xi_n^S \mu_i w_{in} L_{in}, \tag{B.5}$$

$$w_{\ell n} L_{\ell n} = \int_0^{j_n^*} \frac{\gamma_n(j)^{1-\sigma}}{\int_0^1 \gamma_i(j')^{1-\sigma} dj'} Y_n^M dj + \int_0^{j_i^*} \frac{\gamma_n(j)^{1-\varepsilon}}{\int_0^{J_n} \gamma_n(j')^{1-\varepsilon} dj'} Y_n^S dj, \tag{B.6}$$

$$w_{cn} L_{cn} = \int_{j_i^*}^1 \frac{\gamma_n(j)^{1-\sigma}}{\int_0^1 \gamma_n(j')^{1-\sigma} dj'} Y_n^M dj + \int_{j_i^*}^{J_n} \frac{\gamma_n(j)^{1-\varepsilon}}{\int_0^{J_n} \gamma_n(j')^{1-\varepsilon} dj'} Y_n^S dj, \tag{B.7}$$

$$r_n H_n = \sum_{i\in\{\ell,c\}} (1-\mu_i) w_{in} L_{in}, \tag{B.8}$$

$$\mathbb{P}_n = \left[\left(\frac{P_n^M}{\varphi^M} \right)^{1-\alpha} + \left(\frac{P_n^S}{\varphi^S} \right)^{1-\alpha} \right]^{\frac{1}{1-\alpha}}, \tag{B.9}$$

$$\xi_n^k = \frac{\left(P_n^k/\varphi^k\right)^{1-\alpha}}{\left(P_n^M/\varphi^M\right)^{1-\alpha} + \left(P_n^S/\varphi^S\right)^{1-\alpha}}, \tag{B.10}$$

$$\pi_n = \frac{(p_n^M)^{1-\beta}}{\sum_{n'\in\mathcal{R}} (p_n^M)^{1-\beta}}, \tag{B.11}$$

$$P^M = \left[\sum_{n\in\mathcal{R}} (p_n^M)^{1-\beta} \right]^{\frac{1}{1-\beta}} \tag{B.12}$$

$$p_n^M = \frac{1}{A_n^M} \left[\int_0^1 \gamma_n(j)^{1-\sigma} dj \right]^{\frac{1}{1-\sigma}}, \tag{B.13}$$

$$P_n^S = \frac{1}{A_n^S} \left[\int_0^{J_n} \gamma_n(j)^{1-\varepsilon} dj \right]^{\frac{1}{1-\varepsilon}}, \tag{B.14}$$

$$H_n = G_n r_n^{\kappa}, \tag{B.15}$$

$$\sum_{n\in\mathcal{R}} L_{cn} = \bar{L}_c \tag{B.16}$$

C Appendix for Calibration

C.1 Set Parameters and Functional forms (Step #1)

Elasticity of Substitution between Tasks We set the elasticity of substitution between tasks in the production of the manufacturing sector, σ, equal to 0.5. We also assign the same value for the elasticity of substitution between tasks in the production of high-skill services.

Preference First, we set the expenditure share on residential floor space such that $1-\mu_c = 0.15$ for college graduates and $1-\mu_\ell = 0.25$ for non-college graduates following Diamond and Moretti (2024). Second, the elasticity of substitution between manufacturing and high-skill services in consumption, α, is set to 0.5, following the standard value in the macroeconomic literature on structural transformation. Third, among the manufacturing goods, the elasticity of substitution between goods produced by different regions, β, is set to 4, which is in the middle of the estimates of trade literature.

Other Parameters We assign the floor space supply elasticity, κ, by 1.75 based on the estimates of Saiz (2010) for the U.S. cities.

C.2 Solving Equilibrium Prices (Step #2)

Goods Price and Market Clearing The goods market clearing condition implies that labor payment in the manufacturing sector in location i satisfies:

$$w_{cnt}L^M_{cnt} + w^M_{\ell nt}L^M_{\ell nt} = (p^M_{nt})^{1-\beta}(P^M_t)^{\beta-1}X^M_t, \tag{C.1}$$

where aggregate expenditure on manufacturing goods (X^M_t) is:

$$X^M_t = \sum_i \sum_{n\in\mathcal{R}} \xi^M_{nt}\mu_i w_{int}L_{int} \tag{C.2}$$

Averaging out the equations for each location yields:

$$\ln\left[\sum_i w_{int}L^M_{int}\right] - \frac{1}{N}\sum_{n'\in\mathcal{R}} \ln\left[\sum_i w_{in't}L^M_{in't}\right] = (1-\beta)\left[\ln p^M_{nt} - \frac{1}{N}\sum_{n'\in\mathcal{R}} \ln p^M_{n't}\right] \tag{C.3}$$

We let:

$$\overline{p}^M_{nt} = \frac{p^M_{nt}}{\left[\prod_{n'\in\mathcal{R}} p^M_{n't}\right]^{1/N}} \tag{C.4}$$

High-skill Services Market Clearing In the following, we let

$$\widetilde{A}^k_{nt} = \varphi^k_t A^k_{nt} \tag{C.5}$$

refer to adjusted productivity of sector k. Using this, the expenditure share on sector S is:

$$\xi^S_{nt} = \frac{\left(\widetilde{P}^S_{nt}\right)^{1-\alpha}}{\left(\widetilde{P}^M_t\right)^{1-\alpha} + \left(\widetilde{P}^S_{nt}\right)^{1-\alpha}} \tag{C.6}$$

where $\widetilde{P}^S_{nt} = P^S_{nt}/\varphi^S_t$. The market clearing condition for high-skill services in region n implies:

$$w_{cnt}L^S_{cnt} + w_{\ell nt}L^S_{\ell nt} = \frac{\left(\widetilde{P}^S_{nt}\right)^{1-\alpha}}{\left(\widetilde{P}^M_t\right)^{1-\alpha} + \left(\widetilde{P}^S_{nt}\right)^{1-\alpha}}\left(\mu_c w_{cnt}L_{cnt} + \mu_\ell w_{\ell nt}L_{\ell nt}\right) \tag{C.7}$$

Analogously, the expenditure share on sector M is:

$$\xi_{nt}^{M} = \frac{\left(\widetilde{P}_{t}^{M}\right)^{1-\alpha}}{\left(\widetilde{P}_{t}^{M}\right)^{1-\alpha} + \left(\widetilde{P}_{nt}^{S}\right)^{1-\alpha}} \tag{C.8}$$

The market clearing condition for manufacturing goods in region n requires:

$$w_{cnt}L_{cnt}^{M} + w_{\ell nt}L_{\ell nt}^{M} = \frac{\left(\widetilde{A}_{nt}^{M}\right)^{\beta-1}\left(\overline{p}_{nt}^{M}\right)^{1-\beta}}{\sum_{n'\in\mathcal{R}}\left(\widetilde{A}_{n't}^{M}\right)^{\beta-1}\left(\overline{p}_{n't}^{M}\right)^{1-\beta}} \sum_{i}\sum_{n'} \frac{\left(\widetilde{P}_{t}^{M}\right)^{1-\alpha}}{\left(\widetilde{P}_{t}^{M}\right)^{1-\alpha} + \left(\widetilde{P}_{nt}^{S}\right)^{1-\alpha}} \mu_{i} w_{int} L_{int}, \tag{C.9}$$

Summary We solve these equations as follows.

1. First, we normalize $\widetilde{P}_{0}^{M} = 1$ for period 0. Conditional on the data on wages $\{w_{in0}\}$, employment $\{L_{in0}^{k}\}$ and parameters $(\alpha, \mu_c, \mu_\ell)$, we solve equation (C.7) for the adjusted prices for high-skill services $\{\widetilde{P}_{n0}^{S}\}$. In addition, we use equation (C.3) to compute the demeaned price of goods, $\{\overline{p}_{n0}^{M}\}$, given the data on wages and employment. Then, we solve the system of equations (C.9) for adjusted productivity of manufacturing sector $\widetilde{A}_{n0}^{M}$.

2. Next, using the scale T, which reflects the change in price index of goods between period 0 and 1, we set $\widetilde{P}_{1}^{M} = T$ for period 1. We follow the same steps above to obtain adjusted productivity of manufacturing sector, $\widetilde{A}_{n1}^{M}$, and the adjusted high-skill service prices, $\widetilde{P}_{n1}^{S}$, for period 1.

Using the adjusted prices of goods $(\widetilde{P}_{t}^{M})$ and high-skill services $(\widetilde{P}_{nt}^{S})$, the aggregate price index is given by:

$$\mathbb{P}_{nt} = \left[\left(\widetilde{P}_{t}^{M}\right)^{1-\alpha} + \left(\widetilde{P}_{nt}^{S}\right)^{1-\alpha}\right]^{\frac{1}{1-\alpha}} \tag{C.10}$$

C.3 Solving Labor Market Clearing for Task Allocations (Step #3)

We consider the parameterization of productivity in performing tasks. We posit the task performance as follows:

$$z_{\ell t}(j) = \Omega_{\ell t} e^{-\lambda_{\ell} j}, z_{ct}(j) = \Omega_{ct} e^{-\lambda_{c} j}, \quad \lambda_{\ell} > \lambda_{c} > 0 \tag{C.11}$$

Labor Market Clearing for Goods In equilibrium, measure of college graduates (L_{cn}^{M}) and non-college graduates $(L_{\ell n}^{M})$ performing tasks used in manufacturing sector in region n satisfy:

$$\begin{aligned} w_{cnt}L_{cnt}^{M} &= \frac{\int_{j_{nt}^{*}}^{1} \gamma_{nt}(j)^{1-\sigma} dj}{\int_{0}^{1} \gamma_{nt}(j)^{1-\sigma} dj} Y_{nt}^{M}, \\ w_{\ell nt}L_{\ell nt}^{M} &= \frac{\int_{0}^{j_{nt}^{*}} \gamma_{nt}(j)^{1-\sigma} dj}{\int_{0}^{1} \gamma_{nt}(j)^{1-\sigma} dj} Y_{nt}^{M}, \end{aligned} \tag{C.12}$$

where Y_{nt}^M is total value of production of manufacturing sector in n. Rearranging the equations yields:

$$\begin{aligned} w_{cnt}L_{cnt}^M &= w_{cnt}^{1-\sigma}a_{cnt}^{\sigma-1}\left(p_{nt}^M\right)^{\sigma-1}Y_{nt}^M\int_{j_{nt}^*}^1 z_{ct}(j)^{\sigma-1}dj, \\ w_{\ell nt}L_{\ell nt}^M &= w_{\ell nt}^{1-\sigma}a_{\ell nt}^{\sigma-1}\left(p_{nt}^M\right)^{\sigma-1}Y_{nt}^M\int_0^{j_{nt}^*} z_{\ell t}(j)^{\sigma-1}dj, \end{aligned} \tag{C.13}$$

Using the functional forms of task-level performance (C.11), we have:

$$\begin{aligned} \int_{j_{nt}^*}^1 z_{ct}(j)^{\sigma-1}dj &= \frac{\Omega_{ct}^{\sigma-1}}{\lambda_c(1-\sigma)}\left[e^{\lambda_c(1-\sigma)} - e^{\lambda_c(1-\sigma)j_{nt}^*}\right] \\ \int_0^{j_{nt}^*} z_{\ell t}(j)^{\sigma-1}dj &= \frac{\Omega_{\ell t}^{\sigma-1}}{\lambda_\ell(1-\sigma)}\left[e^{\lambda_\ell(1-\sigma)j_{nt}^*} - 1\right] \end{aligned} \tag{C.14}$$

Plugging these into (C.13), we obtain:

$$\begin{aligned} w_{cnt}L_{cnt}^M &= \frac{1}{\lambda_c(1-\sigma)}w_{cnt}^{1-\sigma}\widetilde{a}_{cnt}^{\sigma-1}\left(p_{nt}^M\right)^{\sigma-1}Y_{nt}^M\left[e^{\lambda_c(1-\sigma)} - e^{\lambda_c(1-\sigma)j_{nt}^*}\right], \\ w_{\ell nt}L_{\ell nt}^M &= \frac{1}{\lambda_\ell(1-\sigma)}w_{\ell nt}^{1-\sigma}\widetilde{a}_{\ell nt}^{\sigma-1}\left(p_{nt}^M\right)^{\sigma-1}Y_{nt}^M\left[e^{\lambda_\ell(1-\sigma)j_{nt}^*} - 1\right], \end{aligned} \tag{C.15}$$

where we denote $\widetilde{a}_{cnt} \equiv a_{cnt}\Omega_{ct}$ and $\widetilde{a}_{\ell nt} \equiv a_{\ell nt}\Omega_{\ell t}$. Note that we obtain Y_{nt}^M on the right-hand side of equations (C.15) from the last step.

Labor Market Clearing for High-Skill Services We consider the labor market clearing conditions for high-skill services. The measure of college graduates (L_{cnt}^S) and non-college graduates $(L_{\ell nt}^S)$ in high-skill services satisfies:

$$w_{cnt}L_{cnt}^S = w_{cnt}^{1-\varepsilon}a_{cnt}^{\varepsilon-1}\left(p_{nt}^S\right)^{\varepsilon-1}Y_{nt}^S\int_{j_{nt}^*}^{J_{nt}} z_{ct}(j)^{\varepsilon-1}dj \tag{C.16}$$

and

$$w_{\ell nt}L_{\ell nt}^S = w_{\ell nt}^{1-\varepsilon}a_{\ell nt}^{\varepsilon-1}\left(p_{nt}^S\right)^{\varepsilon-1}Y_{nt}^S\int_0^{j_{nt}^*} z_{\ell t}(j)^{\varepsilon-1}dj, \tag{C.17}$$

where we obtain

$$Y_{nt}^S = \sum_{i\in\{\ell,c\}}\xi_{nt}^S\mu_i w_{int}L_{int} \tag{C.18}$$

from the last step. Using the functional forms of task-level performance, we obtain:

$$\begin{aligned} w_{cnt}L_{cnt}^S &= \frac{1}{\lambda_c(1-\epsilon)}w_{cnt}^{1-\varepsilon}\widetilde{a}_{cnt}^{\varepsilon-1}\left(p_{nt}^S\right)^{\varepsilon-1}Y_{nt}^S\left[e^{\lambda_\ell(1-\epsilon)J_{nt}} - e^{\lambda_\ell(1-\epsilon)j_{nt}^*}\right], \\ w_{\ell nt}L_{\ell nt}^S &= \frac{1}{\lambda_\ell(1-\epsilon)}w_{\ell nt}^{1-\varepsilon}\widetilde{a}_{\ell nt}^{\varepsilon-1}\left(p_{nt}^S\right)^{\varepsilon-1}Y_{nt}^S\left[e^{\lambda_\ell(1-\epsilon)j_{nt}^*} - 1\right], \end{aligned} \tag{C.19}$$

Summary Given parameters in task performance $(\lambda_\ell, \lambda_c)$ and elasticity of substitution between tasks (σ, ϵ) and conditional on wages of college and non-college graduates $(w_{cnt}, w_{\ell nt})$ and employment of college and non-college graduates $(L^M_{cnt}, L^M_{\ell nt}, L^S_{cnt}, L^S_{\ell nt})$, solving the $2N$ equations (C.15) and $2N$ equations (C.19) together yields the unobserved workers' productivity of college and non-college graduates $(\widetilde{a}_{cnt}, \widetilde{a}_{\ell nt})$, the task threshold, j^*_{nt}, and the frontier of tasks, J_{nt}, for each period.

C.4 Estimation of Task-Level Comparative Advantage (Step #4)

Under the parametrization of task performance (C.11), the equilibrium relationship for the task assignment leads to:

$$\ln\left[\frac{w_{cnt}}{w_{\ell nt}}\right] = \ln\left[\frac{\widetilde{a}_{cnt}}{\widetilde{a}_{\ell nt}}\right] + (\lambda_\ell - \lambda_c) j^*_{nt}, \tag{C.20}$$

This implies that the skill premium captured by the wage ratio between college graduates and non-college graduates $(w_{cnt}/w_{\ell nt})$ in region n is decomposed into the contribution of the difference in the task-neutral productivity between college graduates and non-college graduates $(\widetilde{a}_{cnt}/\widetilde{a}_{\ell nt})$ and the task assignment rule between them, j^*_{nt}. When $\lambda_\ell > \lambda_c$, the rightward shift of the threshold (i.e., increase in j^*_{nt}) leads to an increase in the skill premium.

We use equation (C.20) to estimate the parameters of interest, λ_ℓ and λ_c. The steps in Sections C.2 and C.3 allow us to obtain the right-hand side in equation (C.20). Therefore, we estimate the parameters to match their values and observed skill premium in the left-hand side in equation (C.20).

C.5 Inversion of Sector-Level Productivity (Step #5)

First, we already discussed how the goods market clearing conditions are leveraged to obtain the adjusted productivity for the manufacturing sector, $\widetilde{A}^M_{nt}$, such that the observed patterns are rationalized in the equilibrium.

Next, the adjusted price of high-skill service in region n is given by:

$$\widetilde{P}^S_{nt} = \frac{1}{\widetilde{A}^S_{nt}} \left[\left(w_{\ell nt}\right)^{1-\varepsilon} \left(a_{\ell nt}\right)^{\varepsilon-1} \int_0^{j^*_{nt}} z_{\ell t}(j)^{\varepsilon-1} dj + \left(w_{cnt}\right)^{1-\varepsilon} \left(a_{cnt}\right)^{\varepsilon-1} \int_{j^*_{nt}}^{J_{nt}} z_{ct}(j)^{\varepsilon-1} dj \right]^{\frac{1}{1-\varepsilon}} \tag{C.21}$$

When we use the integral of the task performance, rearranging the equation yields:

$$\widetilde{A}^S_{nt} = \frac{1}{\widetilde{P}^S_{nt}} \left[\left(\frac{w_{\ell nt}}{\widetilde{a}_{\ell nt}}\right)^{1-\varepsilon} \left(e^{\lambda_\ell (1-\epsilon) j^*_{nt}} - 1\right) + \left(\frac{w_{cnt}}{\widetilde{a}_{cnt}}\right)^{1-\varepsilon} \left(e^{\lambda_\ell (1-\epsilon) J_{nt}} - e^{\lambda_\ell (1-\epsilon) j^*_{nt}}\right) \right]^{\frac{1}{1-\varepsilon}} \tag{C.22}$$

Summary For each period, we have obtained $\widetilde{P}^S_{nt}$ in Section C.2, and we have backed out task performance $(\widetilde{a}_{\ell nt}, \widetilde{a}_{cnt})$, task threshold j^*_{nt} and task frontier J_{nt} in Section C.3. Therefore, we obtain the unobserved productivity for high-skill services in each region.

C.6 Inversion of Location Advantages in Amenities and Developers (Step #6)

The free mobility condition for college graduates implies that indirect utility of college graduates in region n in period t is:

$$\ln \bar{v}_t = \ln w_{cnt} + \ln b_{nt} - \mu_c \ln \mathbb{P}_{nt} - (1-\mu_c) \ln r_{nt} \tag{C.23}$$

We subtract the average of them and normalize the geometric mean of amenities ($\frac{1}{N}\sum_i \ln b_{nt} = 0$) to obtain the value of amenities in each region:

$$\ln b_{nt} = -\ln \left[\frac{w^c_{cnt}}{\bar{w}_{ct}}\right] + \mu_c \ln \left[\frac{\mathbb{P}_{nt}}{\bar{\mathbb{P}}_t}\right] + (1-\mu_c) \ln \left[\frac{r_{nt}}{\bar{r}_t}\right], \tag{C.24}$$

where we define $\mathbb{P}_t \equiv \left(\prod_n \mathbb{P}_{nt}\right)^{1/N}$ and $\bar{r}_t \equiv \left(\prod_n r_{nt}\right)^{1/N}$ for their geometric means.

Turing to the floor space development, the floor space market cleaning condition implies that the location advantage of developers is:

$$G_{nt} = r_{nt}^{-(\kappa+1)} \sum_{i \in \{\ell, c\}} (1-\mu_i) w_{in} L_{in} \tag{C.25}$$

Summary Conditional on wages of college graduates (w_{cnt}), price index, $\mathbb{P}_{nt}$, inverted in (C.10) and rent (r_{nt}), we use equation (C.24) to compute the value of amenities across regions, b_{nt}, and equation (C.25) for developers' productivity, G_{nt}, across regions.

D Data Details

D.1 Imputation and Crosswalks

The CBP data only provides the number of establishments within a certain range of employment. We first estimate the true values of all missing employment using the disclosed ones through recursive regressions following Acemoglu et al. (2016). Then, we adjust the imputed employment for hierarchical consistency by proportionally expanding or shrinking the employment and apportioning employment in establishments that miss detailed industry codes (i.e., employment in the parent industry was greater than its child-level total) so that higher-level industries consist solely of missing employment in subordinate totals. Then, we assign the grouped industries to the lowest-level subordinate industries (6-digit for NAICS and 4-digit for SIC). We then gradually change all industrial codes to 1987 SIC while doing the assignment again before each conversion.

Apart from some outliers mentioned in the original code of Acemoglu et al. (2016), there were still some underlying issues with the raw data from years earlier than 1986. For certain early years, the total number of establishments was inconsistent with the sum of all ranges, so we replaced the totals with these sums. Additionally, the estimated average employment in each establishment did not always fall within its corresponding range. We overlooked this issue because the subsequent code ensured that the imputed values fell within their bounds. Similar to the years after 2006, employment in a parent-level industry may be lower than its child-level total. We treated this as a statistical error and replaced the parent-level employment with its child-level total to apportion employment as mentioned above.

D.2 Summary Statistics

Table D.1 provides summary statistics of key variables from the CBP and ACS for selected years across CZs in the US. These variables include the number of CZs and employment shares in the manufacturing and service sectors. We further disaggregate these statistics based on the existence of a four-year college within the CZs. A comparison across these two data sources shows that they have a similar coverage of CZs reflected by the number of CZs in each dataset, which shows minor fluctuations over time. The number of CZs with a college presence also remains relatively stable over the years and is comparable across the two sources.

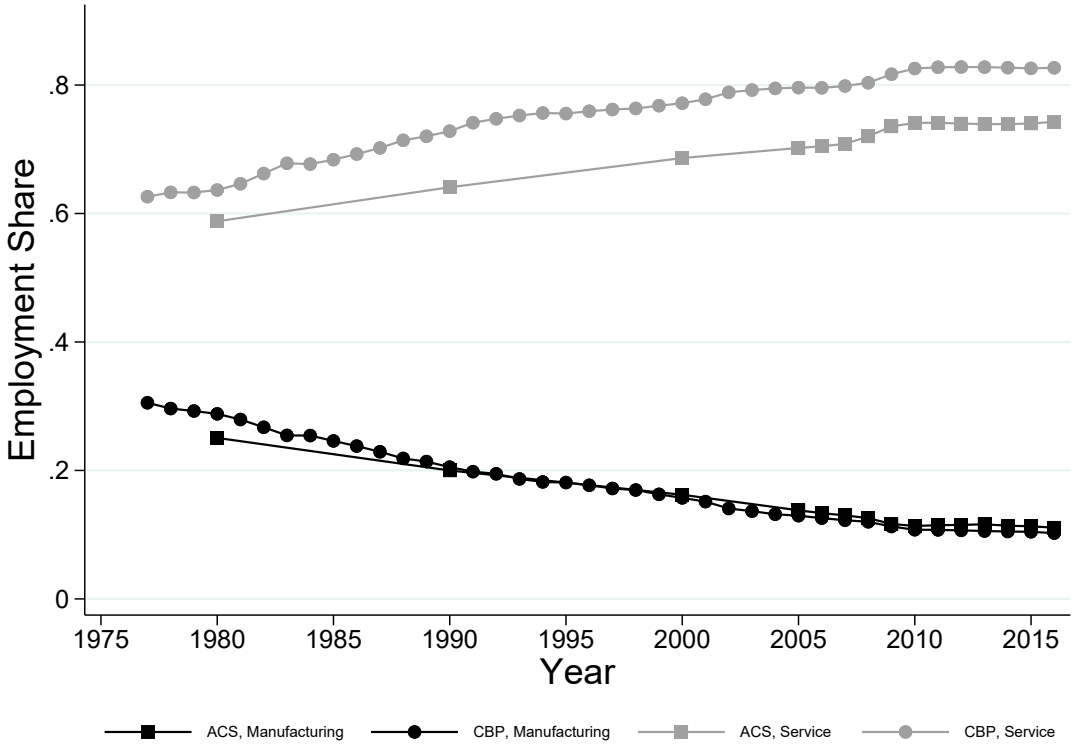
More importantly, Table D.1 and Figure D.1 both demonstrate that local employment statistics in ACS are comparable to those in CBP, even though the ACS employment statistics are derived from individual surveys. Both datasets have captured clear trends of structural transformation from manufacturing to services.

Table D.1: Summary Statistics: CBP vs ACS

	1980 CBP	1980 ACS	1990 CBP	1990 ACS	2000 CBP	2000 ACS	2010 CBP	2010 ACS	2016 CBP	2016 ACS
A. Number of Commuting Zones										
Total	734	699	721	688	740	722	740	722	739	722
With College	429	421	422	413	429	427	429	427	429	427
Without College	305	278	299	275	311	295	311	295	310	295
B. Manufacturing Sector Employment Share										
Average	0.29	0.25	0.21	0.20	0.16	0.16	0.11	0.11	0.10	0.11
Standard Deviation	0.006	0.004	0.005	0.004	0.004	0.003	0.003	0.002	0.004	0.002
With College	0.29	0.25	0.20	0.20	0.15	0.16	0.11	0.11	0.10	0.11
Without College	0.32	0.21	0.28	0.20	0.22	0.19	0.15	0.13	0.15	0.14
C. Service Sector Employment Share										
Average	0.64	0.59	0.73	0.64	0.77	0.69	0.83	0.74	0.83	0.74
Standard Deviation	0.005	0.003	0.005	0.003	0.004	0.002	0.003	0.002	0.003	0.002
With College	0.64	0.59	0.73	0.64	0.78	0.69	0.83	0.75	0.83	0.75
Without College	0.57	0.55	0.64	0.60	0.69	0.60	0.76	0.67	0.76	0.66

Notes: CZs are defined as 1990 Commuting Zones. Average and standard deviation of sector employment shares are calculated as the mean and standard deviation across CZs in a given year. "With College" and "Without College" represent the CZs with and without a four-year or above college in the IPEDS data.

Figure D.1: Average Employment Shares: CBP vs ACS



Notes: This figure plots the average share of employment in manufacturing and services across CZs using ACS and CBP data between 1977 and 2016.

E Additional Empirical Results

In this section, we present additional results that complement the main results in the paper, including a snapshot of Rust Belt regions (E.1), additional results on local structural transformation and its geographic variation (E.2), MSA-level results (E.4), additional identification results (E.5), and the sorting of labor into tasks (E.6).

E.1 Rust Belt Cities

Figure E.1 plots the county-level employment share of high-skill services for four Rust Belt cities: Detroit, Pittsburgh, Milwaukee, and St. Louis. Two findings stand out. First, these historically industrial cities began with relatively small high-skill service sectors, each accounting for less than 25 percent of employment, but subsequently experienced substantial growth in line with the broader national pattern of structural transformation. Second, the expansion of high-skill services varied markedly across these regions: St. Louis and Pittsburgh saw increases of nearly 25 percentage points, whereas Detroit experienced a more modest rise of only 16 percentage points.

E.2 Local Structural Transformation

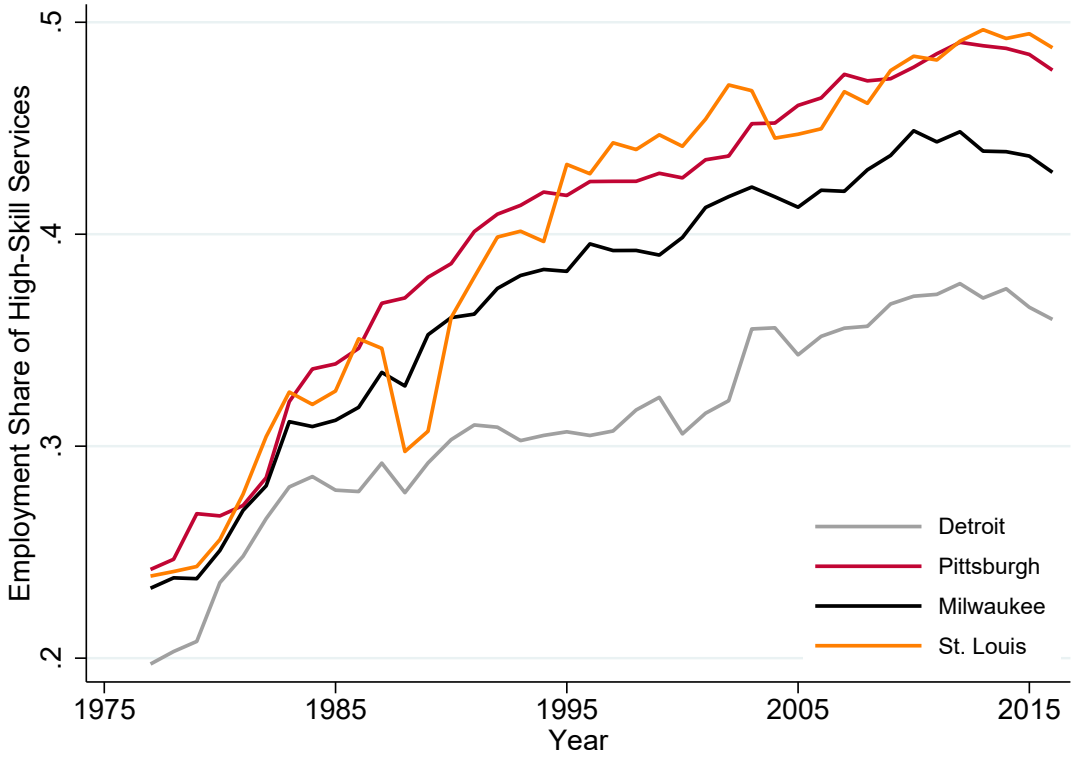
Figure E.2 plots changes in employment shares between 1977 and 2016 across four sectors—manufacturing, high-skill services, low-skill services, and construction—against the log of total employment in 1977. Consistent with well-established patterns, the manufacturing sector experienced a sharp decline, high-skill services expanded significantly, and the construction sector remained largely stable. Beyond these aggregate trends, the figure reveals substantial regional heterogeneity: changes in employment shares within both manufacturing and service sectors vary markedly across CZs. Understanding this variation is a central focus of the paper.

Structural Change by Sector and Location In Figure E.3, we categorize CZs into five groups based on the ranking of the top university in each CZ, where "Rank=1" corresponds to the group containing the top 100 universities according to the US News ranking. We find that CZs with a top 100 university experienced the most rapid increase in service sector employment share. In addition, structural transformation is significantly more pronounced in CZs that have a university included in our ranking list (i.e., the top 440 universities) compared to those without a ranked university, which are classified as "Others."

Removing Education Services Education services may take an exceptional weight in the (high-skilled) service sector in smaller regions, such as small college towns. To alleviate concerns over colleges themselves shaping shifts of the (high-skilled) service sector, we replicate Figure 2 but

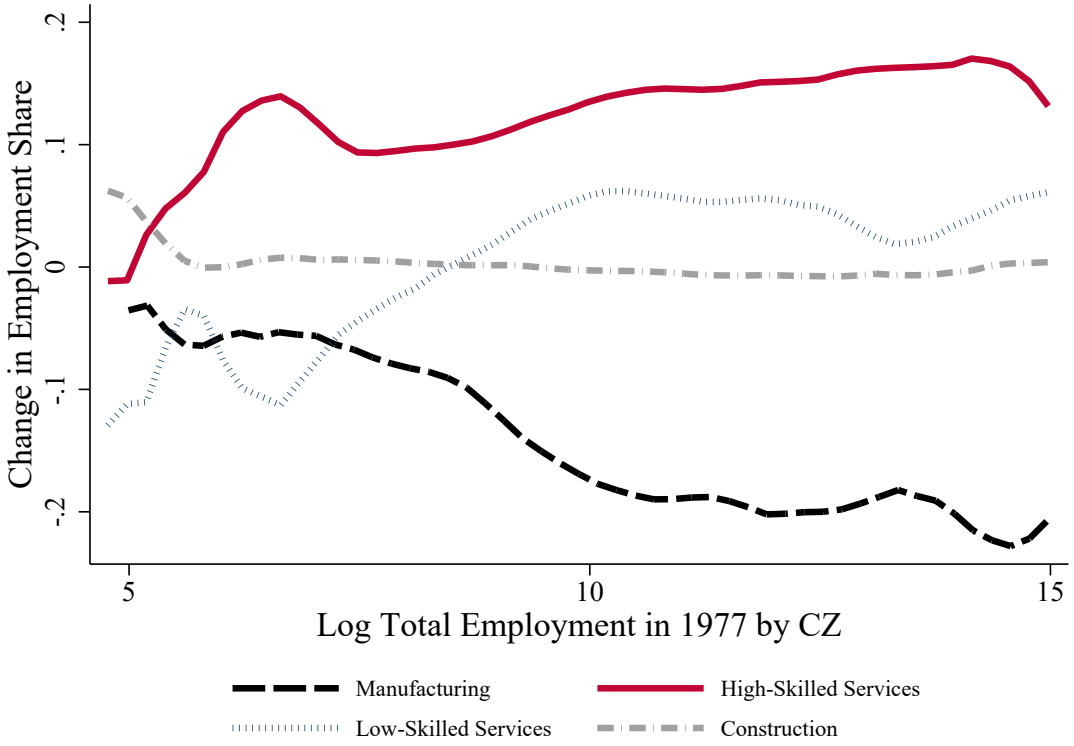
removing "Education Services" from our sample. Unsurprisingly, the results as shown in Figure E.4 are essentially identical.

Figure E.1: High-Skill Services in Rust Belt Cities: 1977-2016



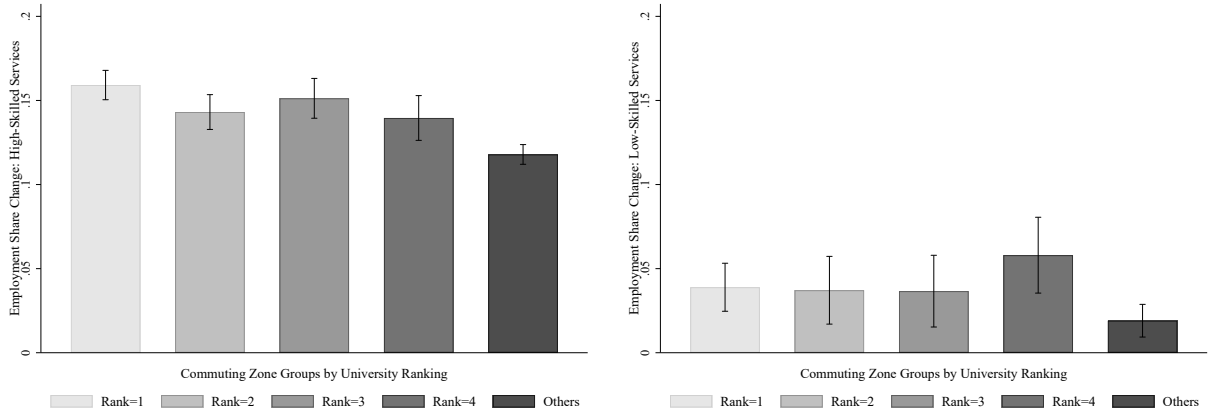
Notes: This figure plots the change in share of employment in high-skill services between 1977 and 2016 across four representative rust belt cities. Data source: CBP.

Figure E.2: Change in Employment Share by Sector and CZ: 1977-2016



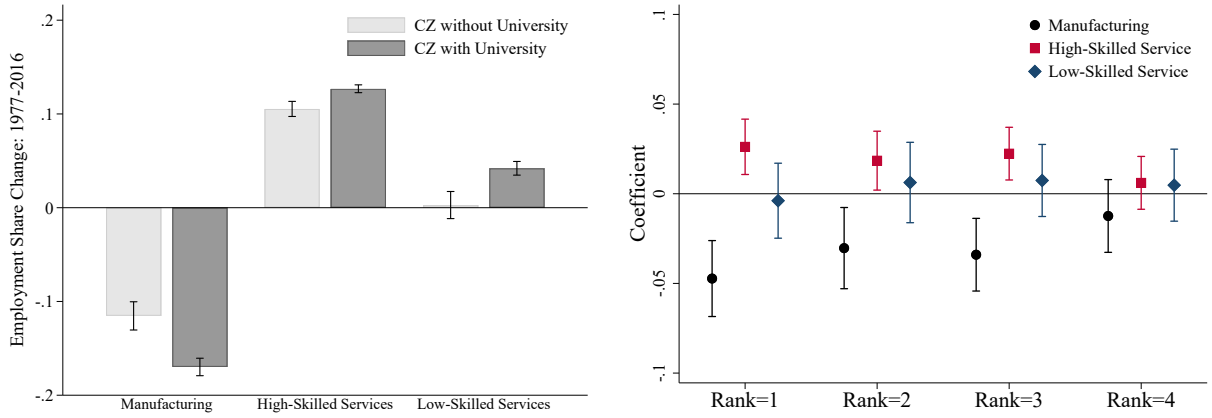
Notes: This figure plots the change in share of employment in manufacturing, low-skill services, high-skill services, and construction between 1977 and 2016 (y-axis), against the log total employment in 1977 (x-axis), across CZs. The lines are generated via local mean-smoothing. Data source: CBP.

Figure E.3: Change in Service Employment Share across University Ranking Groups



Notes: These figures show the average employment share changes for high-skill (left) and low-skill (right) service sectors between 1977 and 2016 across CZs, grouped by the existence of a four-year university in that region. The bars represent the average change in service employment share in each group, and the vertical lines represent their 95 percent confidence intervals. Data sources: CBP and IPEDS.

Figure E.4: Local Structural Transformation without Education Services



(a) Average change in sectoral employment share in CZs with and without universities

(b) Change in sectoral employment share in CZs by university rankings

Notes: These figures show the changes in sectoral employment share between 1977 and 2016 across CZ groups. "Education Services" is removed from the high-skill services; it's otherwise identical with Figure 2.

E.3 Number of Establishments

Besides employment differences, we also find that the number of service sector establishments grew more rapidly in CZs with colleges than those without. In contrast, the number of manufacturing establishments increased through the late 1990s before entering a period of decline.

Figure E.5a depicts the cumulative growth in the average number of establishments in the manufacturing and service sectors across CZs with and without a four-year college from 1977 to 2016. Establishment counts are normalized to their 1977 levels, facilitating a comparison of growth trajectories over time relative to the base year. The figure reveals distinct sectoral trends and a marked divergence between CZs with and without a college presence, particularly in the service sector, where growth is substantially higher in regions hosting a four-year institution.

The service sector experienced substantial growth in both groups of CZs; however, the expansion was significantly more pronounced in regions with a college presence. By 2016, the average number of service sector establishments in CZs with a four-year college had more than doubled relative to 1977, indicating robust growth. Although CZs without a college also experienced an increase, the pace of growth was noticeably slower. This divergence suggests a positive correlation between the presence of higher education institutions and the proliferation of service sector establishments, potentially reflecting the higher concentration of skilled labor and innovation-oriented activities typically associated with college towns.

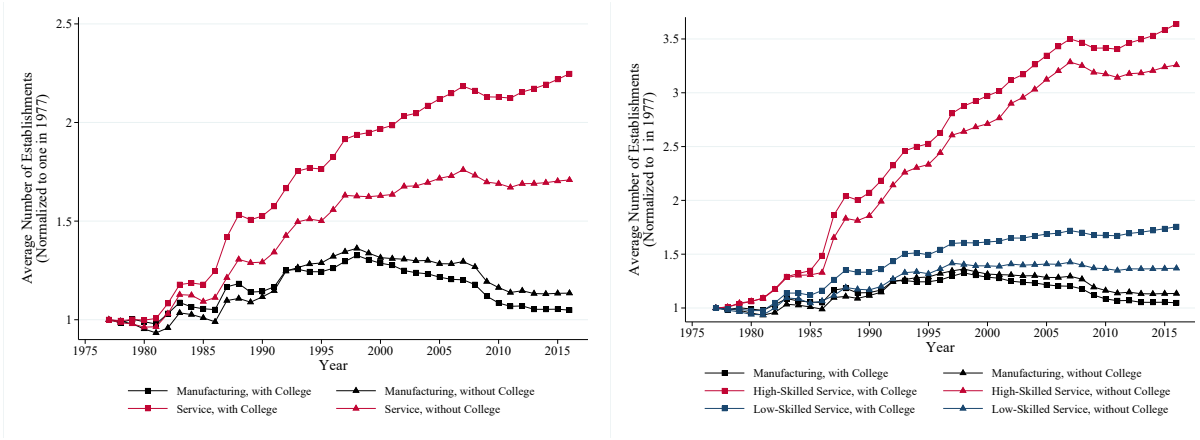
In contrast, trends in the manufacturing sector followed a markedly different trajectory. The number of manufacturing establishments remained relatively stable over the full period, exhibiting minor fluctuations and ultimately returning to levels close to those observed in 1977. Both groups of CZs saw a decline in manufacturing establishments beginning in the late 1990s, consistent with broader structural shifts in the economy away from manufacturing and toward services. Notably, the decline was slightly more pronounced in CZs with a college, further emphasizing the role of educational institutions in shaping the direction and composition of local economic transformation.

In addition to comparing manufacturing and service sectors, as in Figure E.5a, we break down the service sector further into high-skilled and low-skill services. The results are given in Figure E.5b.

E.4 MSA-Level Results

We aggregate the county-level CBP data to the level of metropolitan statistical areas (MSA) and present the corresponding versions of Figure 1 and 2 in Figure E.6 and E.7.

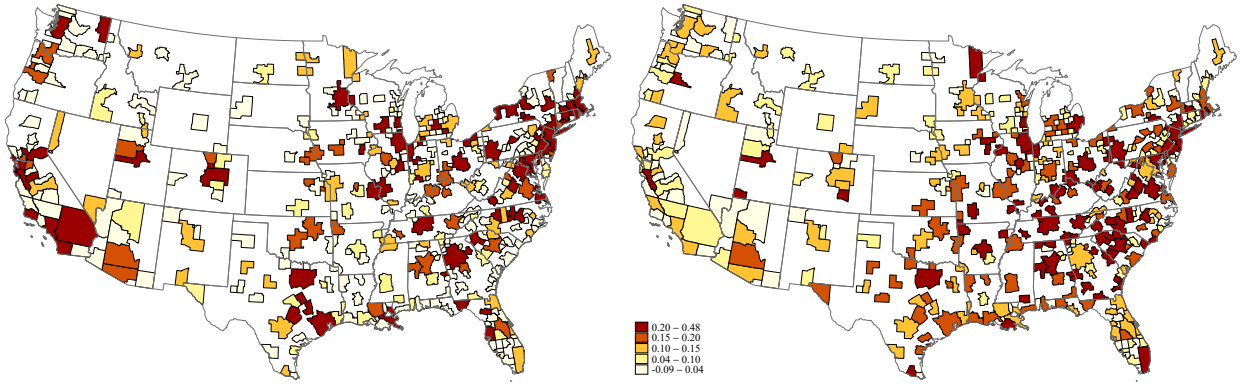
Figure E.5: Average Number of Establishments by Location and Sector



(a) Two Sectors **(b)** Three Sectors

Notes: These figures plot the changes in average number of establishments by sector across CZs with or without college between 1977 and 2016, with 1977 data normalized to one. In Panel (a), the red (black) points and lines show the average number of establishments in the service (manufacturing) sector. In Panel (b), the red, navy, and black lines represent high-skill service, low-skill service, and manufacturing sectors respectively. Within a sector, squares (triangles) are the average number of establishments in that sector for CZs with (without) a four-year university. Data source: CBP.

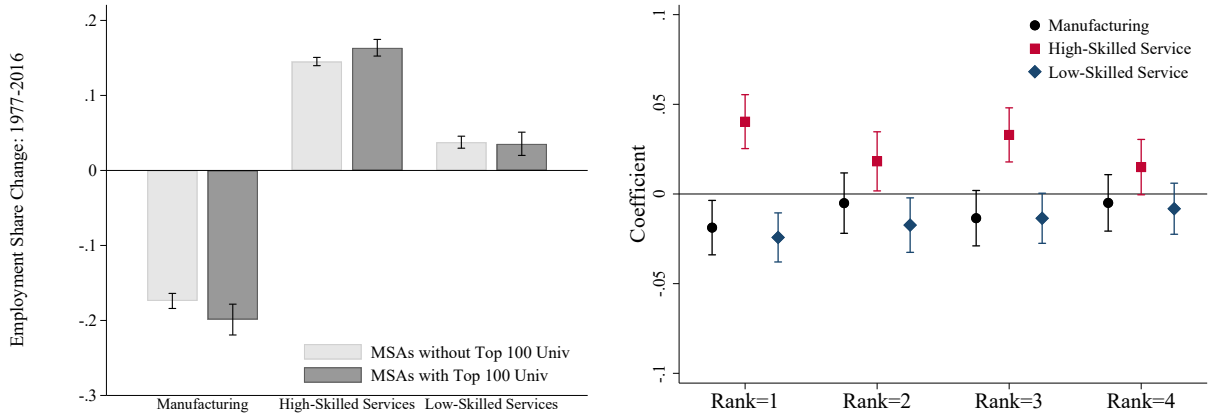
Figure E.6: Geography of US Colleges and Change in Service Employment Share: MSA-Level



(a) US Colleges by Rankings **(b)** Change in Employment Share of Services

Notes: Panel (a) shows the distribution of colleges by their 2016 US News rankings. MSAs are divided into five groups: from dark to light, rank=1 (69 in total); rank=2 (37 in total); rank=3 (45 in total); rank=4 (39 in total); and others (187 in total). Panel (b) illustrates the change between 1977 and 2016 in the share of employment in the service sector across MSAs, divided into five quintiles. Data sources: US News Best National Universities Ranking and CBP.

Figure E.7: Universities and Local Structural Transformation: MSA-Level



(a) Average change in sectoral employment share in MSAs with and without Top 100 universities

(b) Change in sectoral employment share in MSAs by university rankings

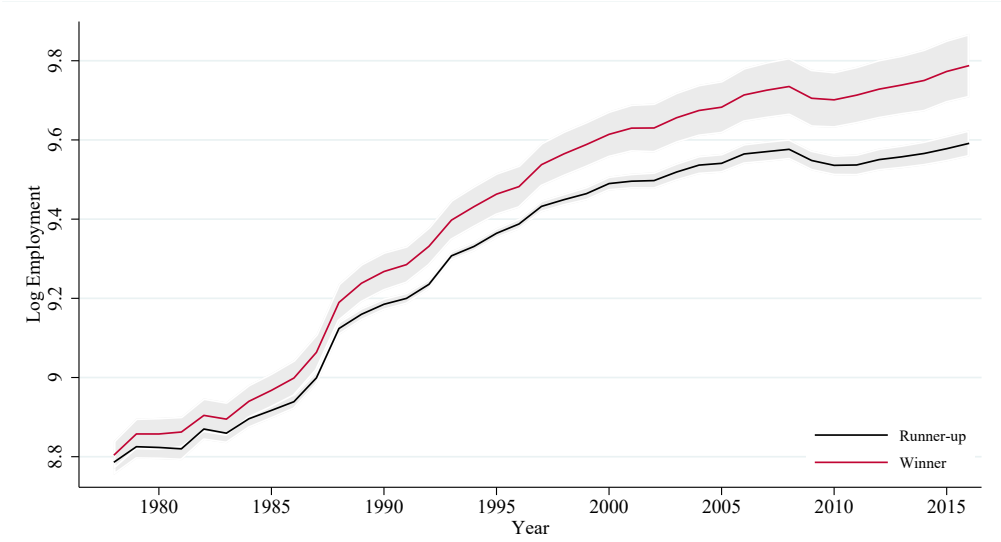
Notes: These figures show the average changes in sectoral employment share between 1977 and 2016 across MSA groups. In Panel (a), MSAs are grouped by the existence of a Top 100 university. Bars represent the average change of sectoral employment share in each group, and the vertical lines represent their 95 percent confidence intervals. In Panel (b), we group MSAs by the existence of a university that falls into each ranking group: "1-100 (rank=1)," "101-200 (rank=2)," "201-300 (rank=3)," "301-440 (rank=4)," and "Others." We regress changes of employment share in the manufacturing and service sectors between 1977 and 2016 on the logarithm of total MSA-level employment in 1977, the sectoral employment share in 1977, and a set of indicators on the rank group of the top university at each MSA. This figure plots the coefficients on these ranking indicators for each sector, together with their 95 percent confidence intervals. Data sources: CBP, IPEDS, and US News Best National Universities ranking.

E.5 Additional Identification Results

As an illustration of our empirical exercise, Figure E.8 plots the dynamics of the logarithm of service sector employment for the winner and runner-up counties. Initially quite similar, the two groups of counties diverged significantly over the four decades, with the winning counties experienced larger overall increases in service employment. This descriptive result aligns with the regression results presented in Table 1.

As a robustness check, Table E.1 presents the regression results when we consider locations initially selected for colleges as "winners" but were later relocated away from these sites. The estimation result does not change materially, with small improvement in p-values.

Figure E.8: Service Employment: Winner versus Runner-up Counties



Notes: The red (black) line displays the logarithm of average employment in services from 1977 to 2016 for the winner (runner-up) counties in the college site selections. The gray-shaded area is the 95 percent confidence interval. Data source: CBP and Andrews (2023).

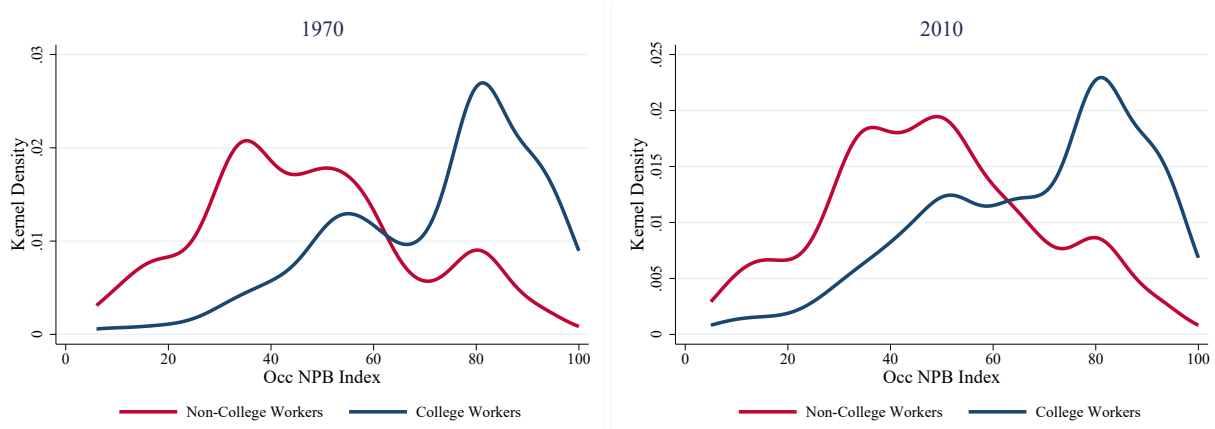
Table E.1: Effects of Winning a College Site Selection

	Manufacturing	Service
Winning Site	-0.010**	0.012**
	(0.004)	(0.005)
Sectoral Employment Share in 1977	-0.621***	-0.629***
	(0.035)	(0.038)
Log Total Employment in 1977	-0.013***	0.019***
	(0.002)	(0.002)
Constant	0.150***	0.375***
	(0.024)	(0.032)
Observations	943	945

Notes: This table reports the coefficient estimates of equation (1). In parentheses are the robust standard errors clustered by county. ***, ** and * indicates significance at the 1, 5 and 10 percent levels, respectively. Different from Table 1, here we include locations initially selected for colleges as "winners" but were later relocated away from these sites.

E.6 Sorting of Labor into Tasks

Figure E.9: Distribution of Occupations



Notes: These figures plot the Gaussian kernel density of the NPB index for occupations using a bandwidth of 5, for college (navy) and non-college workers (red). The data source is ACS.

E.7 Decomposing the Employment Shift to Services

To connect the local labor market dynamics in skills and tasks to local structural transformation, we decompose the change in the employment share of services at the CZ level into two components: (i) changes in the skill components that are accompanied by the assignment of skills to tasks, and (ii) structural change within task and skill. Intuitively, (i) captures the growth in skilled

labor supply relative to the low-skilled, say, as a result of higher education expansion, whereas (ii) captures an example in which high-skilled workers as technicians in the automotive industry in the 1970s transitioned to developers in high-tech services in the 2000s.

We explore the different sources that could contribute to the geographic variation of structural transformation using our local labor market data on skill and occupation in a simple accounting framework. Consider the following decomposition of the employment share of sector j in location i:

$$e_{ij|i,t} \equiv \frac{E_{ij,t}}{E_{i,t}} = \sum_{s\in\text{Skill}} \sum_{o\in\text{Occ.}} \frac{E_{ijso,t}}{E_{it}} = \sum_{s\in\text{Skill}} \sum_{o\in\text{Occ.}} e_{iso|i,t} \cdot e_{ijso|iso,t}$$

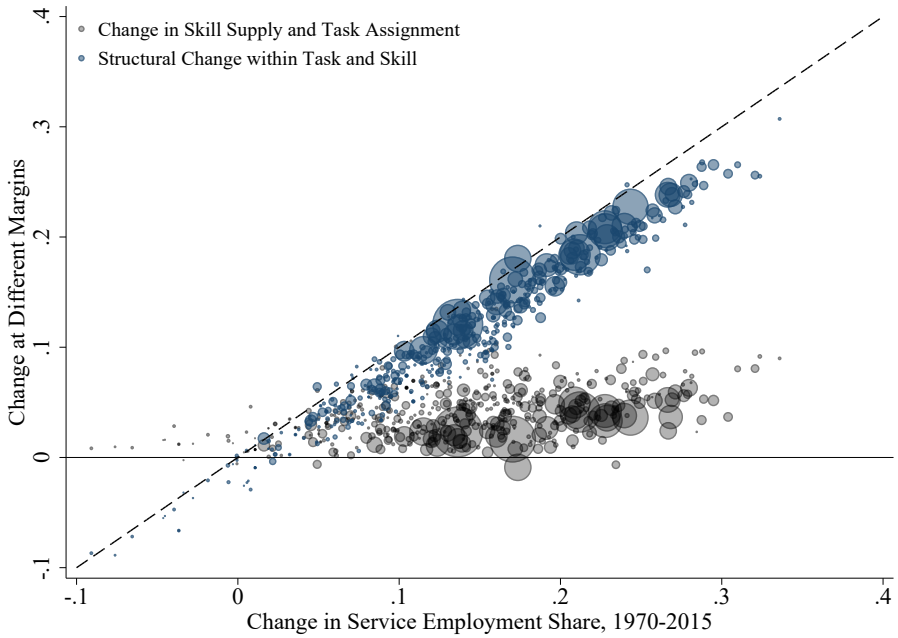
where $e_{iso|i,t} \equiv E_{iso,t}/E_{i,t}$ is the share of employment of skill s and occupation o among all workers in location i; $e_{ijso|iso,t} \equiv E_{ijso,t}/E_{iso,t}$ is the share of workers in industry j among all employees with skill-occupation (s, o) at location i. It follows that

$$\begin{aligned}\Delta e_{ij|i,t} &= \sum_{s\in\text{Skill}} \sum_{o\in\text{Occ.}} \left(e_{iso|i,t} \cdot e_{ijso|iso,t}\right) - \sum_{s\in\text{Skill}} \sum_{o\in\text{Occ.}} \left(e_{iso|i,t-1} \cdot e_{ijso|iso,t-1}\right) \\ &\approx \underbrace{\sum_{s\in\text{Skill}} \sum_{o\in\text{Occ.}} \mathcal{W}^{\mathbb{A}}_{ijso,t-1} \cdot \Delta e_{iso|i,t}}_{\Delta e^{\mathbb{A}}_{ij|i,t}} + \underbrace{\sum_{s\in\text{Skill}} \sum_{o\in\text{Occ.}} \mathcal{W}^{\mathbb{B}}_{ijso,t-1} \cdot \Delta e_{ijso|iso,t}}_{\Delta e^{\mathbb{B}}_{ij|i,t}}\end{aligned} \tag{E.1}$$

In (E.1), the weight terms $\mathcal{W}^{\mathbb{A}}_{ijso,t-1}$ and $\mathcal{W}^{\mathbb{B}}_{ijso,t-1}$ represent the initial employment shares $e_{ijso|iso,t-1}$ and $e_{iso|i,t-1}$. The first component, denoted by $\Delta e^{\mathbb{A}}_{ij|i,t}$, summarizes the changes in the supply of workers with different skill levels in the local labor market, as well as the assignment of workers with specific skills to various occupations. These two parts are aligned with skill-biased structural transformation and task upgrading or downgrading because of technological progress. The second component, $\Delta e^{\mathbb{B}}_{ij|i,t}$, captures the reallocation of workers within the same skill level and occupation to a different sector. For example, a high-skilled researcher in the automotive industry might transition to a research role in the high-tech service sector as manufacturing declines and service rises. Put differently, this component also illustrates changes in task content and skill requirements across sectors over time.

We now show how the each component contributes to the geographic variation in the employment shift to services. Based on the ACS data, Figure E.10 plots them for the service sector (j) across CZs (i) between 1970 ($t-1$) and 2016 (t) in the vertical axis, versus the overall change in employment share in services on the horizontal axis. The size of each circle corresponds to the total employment in each CZ in 1970. Two key observations stand out. First, changes in task assignments for workers with a given skill level and the supply of skills show relatively little variation across CZs, as indicated by the black circles that demonstrate small cross-region differences. Second, the reallocation of workers across sectors within the same skill and occupation, accounts

Figure E.10: Decomposition of Employment Share Changes in Services: 1970-2015



Notes: This figure shows the decomposition of structural transformation at 480 CZs. The horizontal axis represents the change in service employment share between 1970 and 2015; the vertical axis represents each of the two components described by $\Delta e^{\mathbb{A}}_{ij|i,t}$ (in black) and $\Delta e^{\mathbb{B}}_{ij|i,t}$ (in blue). The size of each circle corresponds to the total employment in the CZ in 1970. The dashed line is the 45-degree line. Data source: ACS.

for most of the regional differences. This suggests that the reallocation of tasks across sectors, including the emergence of new tasks concentrated in the service sector, plays a significant role in explaining the geography of structural transformation.

These two channels roughly correspond to the dual role of universities: first, as local *talent hubs* that produce high-skilled labor; and second, as local *innovation hubs* that foster the development of new tasks, particularly within emerging service industries. As talent hubs, universities contribute to the local labor market by producing high-skilled workers. This increased supply of skilled labor over time reduces the cost of human capital for local firms, thereby facilitating sectoral expansion. As innovation hubs, universities push the technological frontier and foster the creation of new tasks and industries. Collaboration with local firms, startups, and government entities accelerates the diffusion of knowledge and facilitates the commercialization of new technologies, fostering the emergence of new sectors and the reallocation of labor across industries. This increases employment opportunities and new business establishments, thereby accelerating the shift to high-skill services. Our decomposition shows that the innovation role accounts for the majority of the geographic variation in structural transformation between 1970 and 2015, whereas changes in the skilled labor supply contribute marginally, consistent with the theoretical and quantitative results.